

Zombies, brains, and tweets

The neural and emotional correlates of social media

September 2013

Introduction

What constitutes audience engagement? What elements of a TV show produce the most social activity? Twitter's ability to capture near real-time audience reactions and sentiment toward television programming has been well documented, but less is known about what content drives an individual to tweet (or conversely, not to tweet). Though common sense may suggest that especially provocative, humorous, or emotional moments generate the most activity on social media, are these moments also the most neurologically stimulating? Researchers at the Harmony Institute [HI] collaborated with neuroscientists at Columbia University and The City College of New York to address these questions using AMC's hit show, *The Walking Dead*, as a case study.

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The rise of social television

Over the last five years, social media has become a powerful platform for capturing audience response to entertainment. Televised spectacles like awards shows, the Olympics, or the US presidential debates generate hundreds to thousands of mentions on social media per second, providing marketers, advertisers, and content-creators with rich streams of emotional reactions in real-time. Subsequently, researchers used these data streams to successfully predict box office revenue for films and ratings of television shows. ¹ Twitter now provides television networks with a set of best practices for “live-tweeting,” encouraging producers to develop unique hashtags and have their stars tweet during episode airings. The company has recently teamed up with Nielsen to create a new metrics for engagement with television. ² The social revolution of television has even led to the altering of a show’s content in response to public commentary. ³

Given the power with which Twitter can seemingly predict the critical and monetary success of entertainment, why do many still contend that social media poorly captures audience engagement?

Despite this rapid transformation of how people engage and interact with televised content, the degree to which social media is an accurate indicator of audience engagement remains unclear—stimulating content may not necessarily encourage sharing, and the absence of chatter may not point to a lack of engagement.

¹ Terrence O’Brien, “Scientists Predict Box Office Revenue With Twitter,” *Switched*, April 3, 2010, <http://www.switched.com/2010/04/03/scientists-predict-box-office-revenue-with-twitter/>. ; Radha Subramanyam, “The Relationship Between Social Media Buzz and TV Ratings,” *Nielsen Newswire*, October 6, 2011, <http://www.nielsen.com/us/en/newswire/2011/the-relationship-between-social-media-buzz-and-tv-ratings.html>. ² Larry Greenmeier, “Nielsen and Twitter Team to Track TV,” 60-Second Tech, *Scientific American*, January 3, 2013, <http://www.scientificamerican.com/podcast/episode.cfm?id=nielsen-and-twitter-team-to-track-t-13-01-03>. ³ John Jannrone, “When Twitter Fans Steer TV,” *Wall Street Journal*, September 17, 2012, <http://online.wsj.com/article/SB10000872396390444772804577623444273016770.html>

What do people share?

One potential reason for this disconnect may be the difference between *stimulating* and *shareable* content. In one study, researchers looked at more than 7,500 articles published in the *The New York Times*, and found those articles that evoked “activating” emotions in readers—like surprise and shock—showed up more often on the Times’ “most emailed” list, even when controlling for a variety of other factors. Conversely, articles that elicited “deactivating” emotions—like sadness—were far less likely to be shared. ⁴

Although that study focused on the news media, the findings have clear implications for entertainment. If people are more inclined to share content that elicits certain emotions, then social media responses to movies and television may similarly privilege particular narrative moments. At the same time, emotional reactions to televised entertainment and, in particular, dramatic fictional content may differ from responses to nonfiction or journalistic accounts of events. Building upon research at the intersection of cognitive and social psychology, as well as communications, gaming and literary theories, we replaced the concept of “activation” with “immersion”—a condition in which a viewer is deeply and personally invested in a narrative, evidenced by an intense, emotional, and even humorous response to a piece of media or content. ⁵ We argue that immersion—or the experience of “getting lost” in a story—is a better metric of engagement than sentiment or activation, which too often ignore the context in which these emotions are expressed.

⁴ Jonah A. Berger and Katherine L. Milkman, “What Makes Online Content Viral?,” [working paper, University of Pennsylvania, 2009, <http://ssrn.com/abstract=1528077>]. ⁵ Researchers have conceptualized the experience of narrative engagement as a cognitive psychological state of absorption in which a reader or viewer of a narrative experiences feelings of being “lost” in a story (Nell 1988), or “transported into a narrative world” (Green & Brock 2000; Gerrig 1993). An individual’s likelihood of transportation into a narrative world may be affected by personal attributes, as well as attributes of the stimulus narrative and context. Studies of this “melding of attention, imagery and feelings” (Green & Brock 2000, 701) suggest that the degree of individual engagement with a story correlates with that individual’s likelihood of being influenced by the narrative’s content. Furthermore, aspects of a story-world that resonate with an individual’s prior real-world experience may augment a story’s impact (Strange 2013).

Using neuroscience to measure engagement

Our first step toward studying the relationship between stimulating and sharable entertainment was establishing a baseline measurement of audience engagement. Recent studies have demonstrated how advancements in neuroscientific research and technologies such as functional magnetic resonance imaging (fMRI) hold promise as tools for measuring audience engagement.⁶ Yet the use of these tools is limited by the unnatural setting in which they are administered, as well as prohibitive costs and low temporal resolution. In contrast, electroencephalography (EEG), which measures electrical activity along the scalp, shows fluctuations in brain states at a much finer temporal resolution. Researchers including Jacek Dmochowski, Jason Sherwin, and Lucas Parra, our partners on this study, have used EEG to measure neural response to stimuli. According to one of their studies, individual brain activity appeared to be synchronized across test subjects in their responses to filmed media and, in particular, to “emotionally activating” content.⁷

⁶ Uri Hasson et. al., “Intersubject Synchronization of Cortical Activity During Natural Vision,” *Science* 303 [2004]: doi: 1634-1640,10.1126/science.1089506. ⁷ Jacek P. Dmochowski et. al., “Correlated components of ongoing EEG point to emotionally-laden attention: a possible marker of engagement?,” *Frontiers in Human Neuroscience* 6 [2012]:112, doi: 10.3389/fnhum.2012.00112.

Study design

Drawing upon these related insights from psychology and neuroscience, we designed a study to compare patterns of social media sharing and neural engagement over the course of a television show. We chose the 90-minute series premiere of *The Walking Dead*, AMC's dramatic television series about the zombie apocalypse, as our test case.

The choice of this show was premised on its popularity, dramatic subject matter, varied emotional content, and critical acclaim. Premiered in 2010, *The Walking Dead* has set numerous viewing records, including netting more than 5.3 total million viewers for the inaugural episode, at the time making it the largest audience for any original series on the network.⁸

Following the research described earlier, we hypothesized the following:

H1: Social media activity is positively correlated with inter-subject neural synchronicity.

Following Berger and Milkman's (2009) insights on stimulating and shareable content,⁹ we hypothesized that, if neural synchronicity could be correlated with engagement, moments of the show that generated increased inter-subject correlation would also generate increased social media activity.

H2: Content that evokes reactions associated with positive immersion is more strongly correlated with social media activity than positive sentiment.

⁸ "AMC Original Series 'The Walking Dead' Garner's Highest 18-49 Delivery for Any Cable Series Premiere for 2010," *The Futon Critic*, November 1, 2010 <http://www.thefutoncritic.com/ratings/2010/11/01/amc-original-series-the-walking-dead-garner's-highest-18-49-delivery-for-any-cable-series-premiere-for-2010-424510/20101101amc01/#W43MkMmxqEgbwHbV.99>.⁹ Berger and Milkman, 2009.

As we noted earlier, using sentiment as a metric for engagement is problematic in that it ignores the context in which these emotions are expressed. In turn, we expected our more nuanced scale of immersion—which took into account an audience’s level of personal involvement with a narrative—would serve as a more accurate indicator of engagement. In the next section, we provide an overview of our three-pronged methodology combining content analysis, social media analysis, and EEG scans.

Methods:

Towards a bridge between neural and social networks

Content analysis

We began by obtaining a copy of the episode “Days Gone By” from iTunes, which we systematically hand-coded, noting the timestamps of the beginning and end of each of the show’s 628 shots. For each of these shots, we also recorded which characters were featured on screen, whether violent acts occurred, and visual treatment, noting elements including framing (e.g., wide angle or close up) and camera movement. This objective classification of on-screen elements provided us with a highly detailed overview of the show, allowing us to report statistics such as:

- 62% of the shots included the main character, Rick.
- 15% of the shots included zombies.
- 7% of the episode featured acts of violence.
- The episode depicted 19 gunshots to the head.

Though shots offered an objective standard with which to categorize various moments of the show, a more capacious narrative unit was needed to link the episode’s content with social media responses. For this, we drew upon the idea of a “scene”—or an aggregate of shots that constituting a distinct narrative event. Using this definition, we proceeded to categorize the show into 188 scenes that formed a total of 16 sequences, or narrative arcs bounded by temporal and spatial shifts.



Figure 1. Distribution of shot and scene length. The majority of shots are less than ten seconds with a mean of 5.1 seconds while scenes follow a slightly more normal distribution centered on a mean of 21 seconds.

Social media analysis

Equipped with a detailed dataset of the show's content, we used the social media analysis platform Crimson Hexagon and Twitter to obtain each of the approximately 19,000 relevant tweets sent out during the hour-and-a-half series premiere on October 31, 2010. Figure 2 displays these tweets over the course of the show, with labels added for moments of the narrative that seemed to elicit spikes in activity. In instances where tweets mentioned the show but didn't reference a particular scene, we cross-referenced the time the tweet posted with what was happening as the episode aired, and weighted them accordingly (i.e., "general" tweets contributed less to each of the scenes they referenced than those which clearly referred to a single scene).

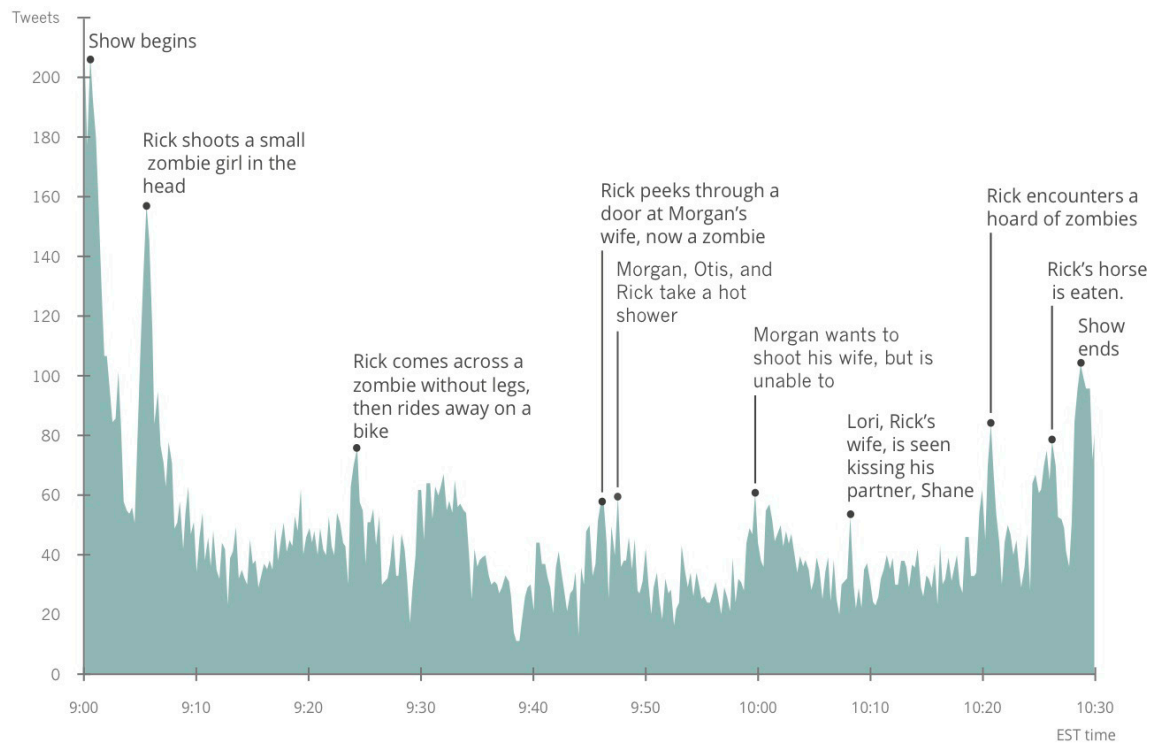


Figure 2. Number of tweets over time

A second dimension of social media analysis involved the identification of emotions embedded within each tweet. Because automatic sentiment classification proved poorly suited to texts of 140 characters or fewer, we developed our own taxonomy for manually categorizing the emotions of responses to the show on Twitter.

We grounded this schema in psychological research, in particular, on J.A. Russel’s Circumplex Model of Affect (1980), which plots the spectrum of emotions onto two dimensions: valence and activation.¹⁰ In Figure 3, a reproduction of a graph from Russell (1980), “valence” represents a scale ranging from displeasure to pleasure, or negative to positive sentiment, while “activation” represents a continuum from sleep to arousal, or no activity to intense activity. While this model imperfectly captures the complexity of human emotion, it provided a set of relatively objective standards that guided our hand labeling of tweets.

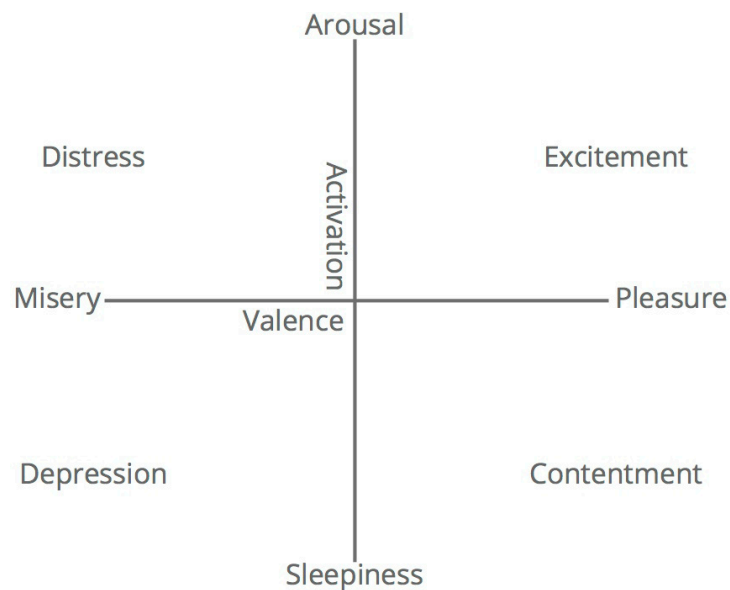


Figure 3. Based on “A Circumplex Model of Affect,” by J. A. Russell, 1980.¹¹

Using this typology as our guide, we coded each tweet on a three-point scale for “sentiment” and “intensity.” Sentiment was measured by emotional content while intensity was measured by grammatical signals, including capital letters, expletives, and exclamation points. In addition to these two emotional components, we were interested in a number of other factors: Did the message comment on the actor’s abilities or the show’s production values? Was the viewer personally affected by the content?

¹⁰ James A. Russell, “A Circumplex Model of Affect,” *Journal of Personality and Social Psychology* 39, no. 6 [1980]: 1164.

¹¹ Ibid.

Was the tweet intended as humorous? Therefore, we also included binary variables for “personal” (0 = no, 1 = yes), “show” (0=no, 1=yes), and “humor” (0=no, 1=yes), in order to approximate a viewer’s level of immersion with the subject material referenced. To estimate the level of immersion expressed in each message, we developed an algorithm that weighted all possible combinations of “sentiment,” “show,” and “personal,” assigning positive values to emotional comments expressing personal investment in the narrative and negative values to matter-of-fact commentary on the show. These weights were then amplified if the tweet also scored high for intensity or was humorous.

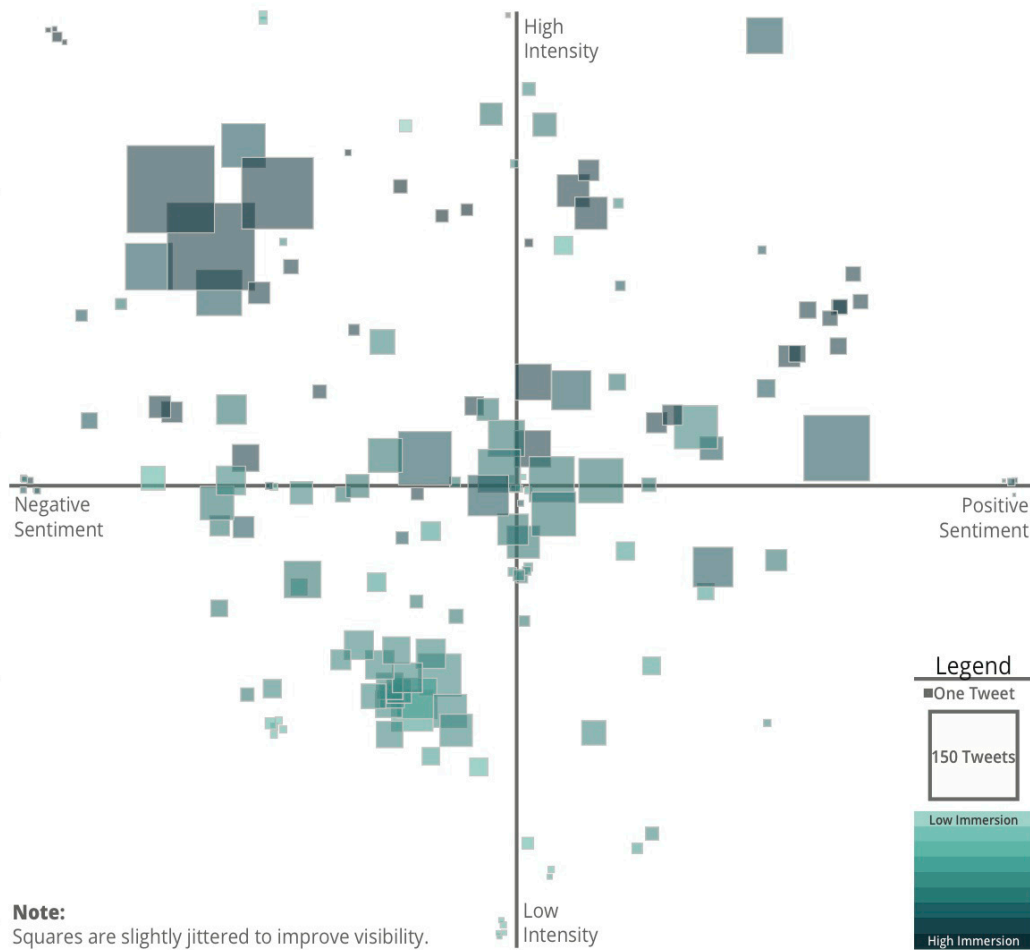


Figure 4. Interplay of emotion, immersion, and social media activity at the level of the scene, replicating the layout of Figure 3, with sentiment on the x-axis and intensity on the y-axis. Each square represents a scene in the show. The squares are sized by the number of tweets about the scene and colored by immersion. In this chart we see a cluster of scenes that evoked a high number of intense, negative reactions and also scored high for immersion.

EEG scans

The final component of our methodology entailed the use of electroencephalography (EEG) data as a proxy measure for audience engagement, for which we collaborated with bioengineers Jacek Dmochowski and Lucas Parra of City College of The City University of New York, as well as Jason Sherwin from Columbia University's biomedical engineering department. We mined the profiles of Twitter users in our sample for gender, age, and location, and recruited subjects to match this group's demographics—predominantly young, urban, males.

Using EEG headsets to measure the 20 subjects' brain activity as they watched the 90-minuted episode, we collected a dataset of roughly 11,000 observations of neural responses to the television show. The resulting, filtered neural data was operationalized through an innovative statistical technique pioneered by Dmochowski et. al. (2012) called component analysis. This method correlates patterns of brain activity across the sample to indicate shared neural response to the stimulus across subjects, making it unlikely that the measurements were unrelated brain activity.

Results

Methodology

We tested our two hypotheses through regression analysis, in models with our outcome variable set to number of tweets per scene, and each tweet weighted by the total number of scenes mentioned in the message. A control was added for the duration of each scene to account for the effect of our subjective classification of these narrative moments. EEG data was expressed through the three highest correlated components of neural activity throughout the show.

The emotions embedded within each tweet were operationalized as per-scene-averages. Finally, we added controls for the presence of shots that feature zombies or violence within a scene. These were included to ensure that any detected effect was not simply the product of content unique to a show about the zombie apocalypse. While it was difficult to reconcile the temporal resolution of these different data sources, we took steps to ensure our results were valid. Summary statistics and regression results are available in the appendix. More in-depth analysis is available upon request.

Neural engagement and social response

First, we assessed the degree to which neural engagement predicts social response. We found that, in general, one frequency of brain wave activity is a significant predictor of tweets, even when controlling for scene length and the presence of zombies and violence.

To further confirm these results, we also tested how the effect size of neural engagement changes in moments with especially high correlations. Echoing past research findings that indicate that spikes in correlated brain activity occur alongside especially engaging content, we saw the effect size crescendo for scenes which feature extreme moments of synchronicity and diminish as these levels subside, offering compelling evidence that spikes in neural synchronicity are correlated with social response.

Emotion, immersion, and social response

Examining the relationship between the overall emotional reaction to a scene and the level of associated social media activity, we found that, all else constant, moments of the show that generated higher levels of intense, humorous, or personal reactions produced a significantly higher level of overall social media activity.

Of these, personal involvement in the show's narrative elicited the strongest effect; shifting from a scene that generates no personal reactions to one that generates all personal reactions should increase the rate of tweets for that scene by a significant factor. We also saw that commentary on the show with regards to a particular scene is significantly and positively correlated with social media activity. Interestingly, in this model, positive sentiment is inversely correlated with tweet frequency.

We further explored the relationship between sentiment and commentary on the show by examining the interactions between these two variables. While we caution against over-interpreting this result—only 5 percent of tweets in the sample were coded for *both* positive sentiment and commentary on the show—we believe this finding provides cautionary evidence against the use of positive sentiment as an indicator of social media engagement. Indeed, from these results, we would suspect that scenes that elicit negative commentary about the show's production actually lead to more tweets than those that evoke reactions of praise.

Finally, we replaced all emotional indicators with our metric for immersion. As hypothesized, this algorithmic combination of “intensity”, “sentiment”, “personal”, “humor”, and “show” is strongly and significantly correlated with social media activity, even when controlling for neural synchronicity and other relevant content variables.

Visualization tool

We supplemented our statistical analyses of the data with custom-built software to facilitate comparison of brain and social media data with the content of the episode (Figure 6). Designed by HI's Graham Technology Fellow Clint Beharry, the program displays annotated neural data and tweets synched with the show's timeline, along with content categories from HI's coding scheme. The visualization of all of the data together on one timeline allows for a more sequential analysis than traditional statistics. For example, a user can see a brain spike when a little zombie girl is shot in the head, then see how tweets occurring after start with high intensity negative sentiment (shock, grossness), then quickly follow with positive sentiment humor (jokes to relieve tension). Animated, 3D design features reference the coded Twitter content by representing more and less "immersed" as well as "humorous" message content.

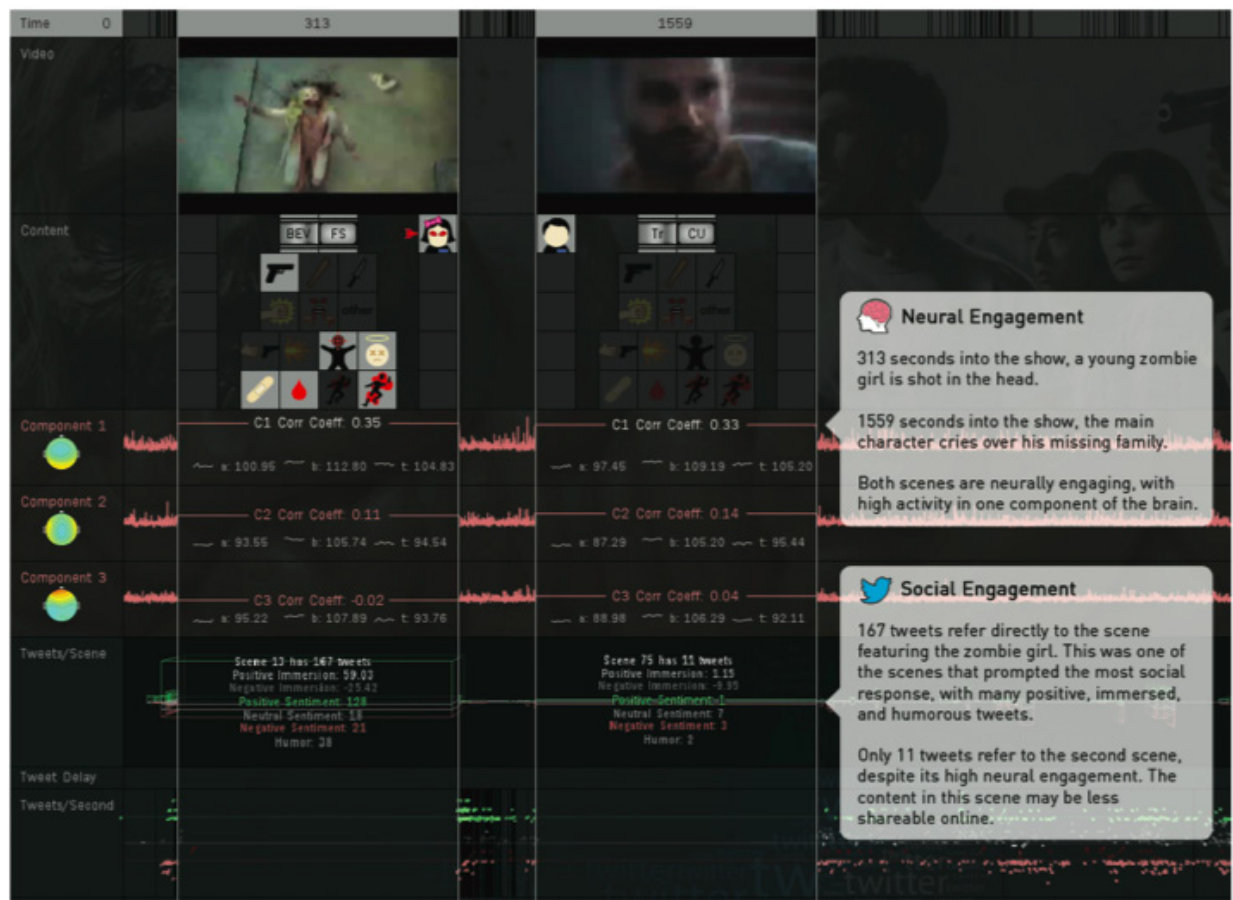


Figure 6. A screenshot of HI's custom built data visualization software. In descending order, we can see: Video footage from the show, coding for on-camera content, EEG data, coding for social media content, and tweet visualization.

Discussion

Our results show preliminary evidence of a link between neural stimulus and social response. With further refinement and replication, content creators or producers could harness these methods to forecast the moments of their shows that will elicit the most discussion on social media. In time, researchers could use the methods outlined in this paper to isolate the neural signatures of various psychographic or demographic clusters and predict how these audience segments will respond to narrative moments differentially on social media.

A more immediate outcome of these results is an empirically based critique of sentiment as the preferred metric for audience engagement on social media. In the context of entertainment, the emotional valence of reactions seems to be meaningless without considering the particular context in which these emotions are expressed. As this study demonstrated, negative comments about a scene were actually one of the strongest predictors of overall social media activity; the act of communicating a response to the show suggests engagement with the content, regardless of accompanying sentiment. Rather than relying on easily implementable sentiment classification algorithms, entertainment-focused social media analysts should strive to develop metrics that more accurately capture audience engagement or immersion.

Ghost engagement

In spite of our positive results, the relative weakness of the effect sizes led us to qualitative methods to further assess the exceptions to our model. In particular, we wondered what factors were associated with scenes that were neurally engaging but people didn't tweet about—a phenomenon we deem “ghost engagement.” As discussed, many of the top neurally engaging scenes also generated many tweets. However, a major exception was a series of scenes involving a car chase and shootout towards the beginning of the show. While these scenes produced many spikes in brain activity, they saw relatively few tweets.

We suspect this may have something to do with the fact that these moments did not involve zombies—a novel element of the show that users were most likely predisposed to tweeting about. On the flip side, a series of scenes towards the end of the show involving a horse being eaten by zombies received nearly one third of all tweets in our sample yet produced no spikes in neural synchronicity. This disconnect between neural engagement and social response is most likely due to the jarring nature of the scene. Furthermore, this scene generated an overwhelmingly amount of negative sentiment as a large number of people were horrified by the depiction of an innocent horse being eaten by a horde of zombies.

Finally, several highly emotional scenes — one of a main character sobbing, believing his family to be dead, and one of a supporting character crying in response to seeing his mother as a zombie — were characterized by very few tweets, but high levels of neural synchronicity. These anecdotes suggest support for Berger and Milkman’s hypothesis that emotionally deactivating content discourages sharing, though we would caution against drawing conclusions in the absence of objective schema for classifying the emotional characteristics of each scene.

Conclusion

By combining neuroscience with content and social media analysis, this study offers a unique perspective on the question of what constitutes audience engagement. In particular, it outlines an innovative methodology that enables the rigorous comparison of narrative elements, neural synchronicity, and social response throughout the course of a television show. In applying this methodology to the series premiere of *The Walking Dead*, we found that neural synchronicity is significantly correlated with social response. This relationship appears to be especially strong in moments when the audience's neural signals spike concurrently. The correlation of these two indicators suggests that their combination may lead to more meaningful metrics of audience engagement.

Looking at the emotions elicited by the show, our models suggest that scenes which evoke intense personal and/or humorous reactions to content are strongly associated with more activity on Twitter, even when controlling for neural synchronicity and relevant content variables. Interestingly, scenes that generate negative commentary about the show are far more likely to generate social media activity than those that evoke positive comments about the show. This suggests that the use of sentiment as an indicator for audience engagement is potentially unfounded, as it ignores the context in which these emotions are expressed. Finally, by combining emotional indicators into an index of immersion that weights intense comments expressing personal investment in the narrative over matter-of-fact commentary on the show, we find that immersion is a strong predictor of social response. We hope this finding opens a path for the development of better schemas for classifying emotions embedded in social media messages.

However, while our models suggest a link between neural synchronicity and social response, the effect size is relatively weak. Further investigation through a visual representation of our data sources reveals anecdotal evidence for the presence of “ghost engagement,” or moments of the show that are neurally stimulating but do not generate much activity on Twitter (or vice versa). While we speculate that these examples are explained by the emotional salience

or novelty of the content in these scenes and/or their temporal placement, further research is required before we can make any definitive conclusions. Here, the development of methodologies and taxonomies for rigorously classifying the emotions evoked by a narrative will be particularly useful.

Appendix

Below you'll find the summary statistics and regression results from our EEG and social media data. A paper containing an in-depth discussion of our analysis and results is available by request. For access, please email info@harmony-institute.org.

Table 1. Summary statistics

Variable	N	Min.	Q1	Med.	Mean	Q3	Max.	Std. Dev
tweets per scene	188	0.00	1.80	8.00	23.40	25.20	202.00	36.20
- weighted	188	0.00	0.67	2.90	10.30	8.90	169.00	21.90
scene duration	188	1.40	9.60	17.20	20.90	28.10	90.80	15.90
intensity*	1947	0.00	1.00	1.00	1.20	2.00	2.00	0.67
- per scene	188	0.00	0.55	1.00	0.89	1.30	2.00	0.56
sentiment*	1947	-1.00	-1.00	0.00	-0.21	1.00	1.00	0.83
- per scene	188	-1.00	-0.38	0.00	-0.11	0.00	1.00	0.43
show*	1947	0.00	0.00	0.00	0.20	0.00	1.00	0.40
- per scene	188	0.00	0.00	0.15	0.25	0.43	1.00	0.29
personal*	1947	0.00	0.00	0.00	0.15	0.00	1.00	0.36
- per scene	188	0.00	0.00	0.06	0.09	0.15	0.53	0.12
humor*	1947	0.00	0.00	0.00	0.26	1.00	1.00	0.44
- per scene	188	0.00	0.00	0.12	0.18	0.31	1.00	0.21
immersion*	1947	-2.60	-0.73	0.38	0.00	0.76	1.90	1.00
- per scene	188	-2.30	-0.52	-0.06	-0.19	0.10	1.20	0.54
zombie[s]	628	0.00	0.00	0.00	0.18	0.00	1.00	0.39
violence	628	0.00	0.00	0.00	0.08	0.00	1.00	0.27
first component	7862	-0.07	-0.01	0.01	0.02	0.05	0.45	0.05
second component	7862	-0.07	-0.02	0.00	0.01	0.03	0.31	0.04
third component	7862	-0.07	-0.02	0.00	0.01	0.03	0.29	0.03

* included for comparison; regressions use per-scene averages as inputs.

Table 2. Simple EEG model

Coefficient	IRR	Estimate	Std. Error	T-Value	P-Value
[Intercept]	4.46	1.50	0.07	19.82	0.00
first component	1.57	0.45	0.19	2.33	0.02
second component	0.69	-0.37	0.18	-2.02	0.04
third component	1.12	0.11	0.20	0.55	0.58
violence	2.99	1.10	0.10	11.08	0.00
zombie(s)	3.71	1.31	0.05	25.85	0.00
scene duration	3.50	1.25	0.09	14.24	0.00

Table 3: Added emotional variables

Coefficient	IRR	Estimate	Std. Error	T-Value	P-Value
[Intercept]	2.04	0.71	0.06	12.40	0.00
first component	1.41	0.35	0.14	2.40	0.02
intensity	5.46	1.70	0.06	29.03	0.00
sentiment	0.27	-1.31	0.07	-19.85	0.00
humor	3.33	1.20	0.08	14.67	0.00
personal	12.03	2.49	0.06	40.38	0.00
show	1.29	0.26	0.05	4.91	0.00
zombie(s)	1.57	0.45	0.04	11.01	0.00
violence	4.64	1.53	0.07	21.50	0.00
scene duration	1.28	0.24	0.07	3.60	0.00

Table 4. Added interaction

Coefficient	IRR	Estimate	Std. Error	T-Value	P-Value
[Intercept]	1.08	0.08	0.07	1.21	0.23
first component	1.37	0.32	0.14	2.27	0.02
intensity	8.71	2.16	0.06	34.50	0.00
sentiment	0.83	-0.18	0.09	-2.04	0.04
humor	2.34	0.85	0.08	10.41	0.00
personal	11.28	2.42	0.06	40.46	0.00
show	7.48	2.01	0.11	18.42	0.00
zombies[s]	1.57	0.45	0.04	11.37	0.00
violence	4.05	1.40	0.07	20.23	0.00
sentiment : show	0.02	-3.81	0.23	-16.85	0.00
scene duration	1.26	0.23	0.07	3.53	0.00

Table 5. Immersion Model

Coefficient	IRR	Estimate	Std. Error	T-Value	P-Value
[Intercept]	1.32	0.28	0.08	3.38	0.00
first component	1.52	0.42	0.17	2.47	0.01
immersion	7.16	1.97	0.11	18.21	0.00
violence	3.31	1.20	0.09	13.72	0.00
zombie[s]	2.68	0.99	0.05	20.99	0.00
scene duration	3.72	1.31	0.08	16.75	0.00

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About HI

The Harmony Institute (HI) is an interdisciplinary research center that studies the impact of entertainment media on the individual and society. We draw on the methods and concepts of the humanities, data, and social sciences to gain insights on the portrayal, dissemination, consumption, and translation of media messages into individual and collective belief and action. Our work ranges from applied media research to university partnerships on studies exploring fundamental questions around the nature of audience engagement and societal impact.

HI was founded by John S. Johnson (BuzzFeed, EYEBEAM, and the Screenwriters Colony) in 2008. After years in the film industry, Johnson recognized the need to better understand entertainment's impact on audiences. HI was formed out of a desire to see entertainment meet the pressing needs of society, and to build a bridge between the worlds of mass media and science.

HI has evaluated entertainment projects ranging from social issue documentaries to fictional TV movies and multi-platform campaigns, and has conducted research on behalf of the Ford Foundation, MTV, and Free Press, among others. Media coverage of Institute work has included profiles in *Science*, the *New York Times*, *Fast Company*, and *GOOD*.

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