Emotional Amplification During Live Streaming: Evidence from Comments During and After News Events

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Live streaming services allow people to concurrently consume and comment on media events with other people in real time. Durkheim's theory of "collective effervescence" suggests that face-to-face encounters in ritual events conjure emotional arousal, so people often feel happier and more excited while watching events like the Super Bowl with family and friends through the television than if they were alone. Does a stronger emotional intensity also occur in live streaming? Using a large-scale dataset of comments posted to news and media events on YouTube, we address this question by examining emotional intensity in live comments versus those produced retrospectively. Results reveal that live comments are overall more emotionally intense than retrospective comments across all temporal periods and all event types examined. Findings support the emotional amplification hypothesis and provide preliminary evidence for shared attention theory in explaining the amplification effect. These findings have important implications for live streaming platforms to optimize resources for content moderation and to improve psychological well-being for content moderators, and more broadly as society grapples with using technology to stay connected during social distancing required by the COVID-19 pandemic.

CCS Concepts: • **Information systems** → *Internet communications tools*; *Chat*.

Additional Key Words and Phrases: live streaming, YouTube Live, shared-attention, emotions, mood, emotional contagion

ACM Reference Format:
Mufan Luo, Tiffany W. Hsu, Joon Sung Park, and Jeffrey T. Hancock. 2020. Emotional Amplification During Live Streaming: Evidence from Comments During and After News Events. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW1, Article 47 (September 2020), 19 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Collective gatherings or shared experiences are usually characterized as members of a society coming together to engage in ritual events simultaneously. Synchronization with shared symbols and emotions in these events can increase emotional intensity. This phenomenon is first noted in Durkheim (1912)'s model of "collective effervescence [9]," along with the model's prediction of the social functions of affect, including a revived sense of social cohesion and social belief. With a

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2573-0142/2020/9-ART47 $15.00
https://doi.org/10.1145/1122445.1122456

focus on emotions, we examine whether collective gatherings change the affective dynamics in a mediated media space, such as live streaming. In the recent years, live streaming platforms such as Twitch, Periscope, Facebook and YouTube Live have become increasingly common as a medium for information sharing on topics ranging from entertainment to news events, and as an avenue for civic engagement [52]. These platforms allow people to remotely attend to the same media with others simultaneously and foster social interaction between co-viewers. Despite a burgeoning literature on live streaming in the context of entertainment, less is known about live broadcast media events through live streaming platforms and their emotional dynamics. The question of how technology affects our collective emotions has renewed urgency given the COVID-19 pandemic, and when such emergency situations require the practice of social distancing and the use of technology to stay connected.

Our research has two overarching goals. The first is to examine whether people's emotional responses to live streamed media events are more intense than the responses to the same event after the live streaming has ended - a phenomenon termed "emotional amplification." Second, we draw on two theoretical frameworks to understand when this amplification takes place and the potential underlying mechanisms. The collective emotions perspective [16, 19, 22, 53, 54] argues that emotional intensity increases during collective relative to individual experiences through exposure to emotional expressions and group identification. The shared attention perspective [43–45], in contrast, posits that having a shared experience can elicit an enhanced experience due to more attentional resources available for the co-attended stimulus.

We report on a text data analysis of comments on live broadcast media events (e.g., political speeches, the Royal Wedding, Notre-Dame de Paris fire) on a live streaming platform - YouTube Live. As suggested by prior work [16], we compared emotional responses to media events between viewers who were each experiencing the media event individually (i.e., retrospective comments) and those who were experiencing the event with others (i.e., live comments). Since language reflects social psychological processes about communicators [33], we analyze the emotional intensity of language produced in live and retrospective comments to provide theoretical insight into why live streaming facilitates emotional intensification by comparing predictions from the collective emotion and shared attention perspectives. Finally, we end with discussions on the implications of our findings for the HCI community and for the live streaming platforms that need to consider the emotional dynamics of different forms of media experiences online.

2 RELATED WORK

2.1 Live streaming on YouTube

Live streaming refers to technology that can "broadcast video to a remote audience in the instant that it is captured [26]." Live streaming services are an important recent form of social media that allows for synchronous consumption of live broadcasting media and instant online communication [55].

2.1.1 Affordances on YouTube Live. Live streaming platforms (e.g., Facebook and YouTube Live, Twitch, Periscope) offer affordances of broadcasting live audio-video and synchronous text messaging in the Internet Relay Chat (IRC) window for all viewers (e.g., [50, 55]). This live streaming service was first introduced to the YouTube platform in 2011 and has garnered wide use among the regular users of YouTube. YouTube Live shares several affordances with other live streaming platforms, such as an IRC window appearing next to the video streaming panel where people communicate in real time as they watch the live media. However, after the live streaming ends, the video can be archived and allow for comments posted in a separate section below the video (see Figure 1). The co-existence of live and retrospective comments for the same video creates an

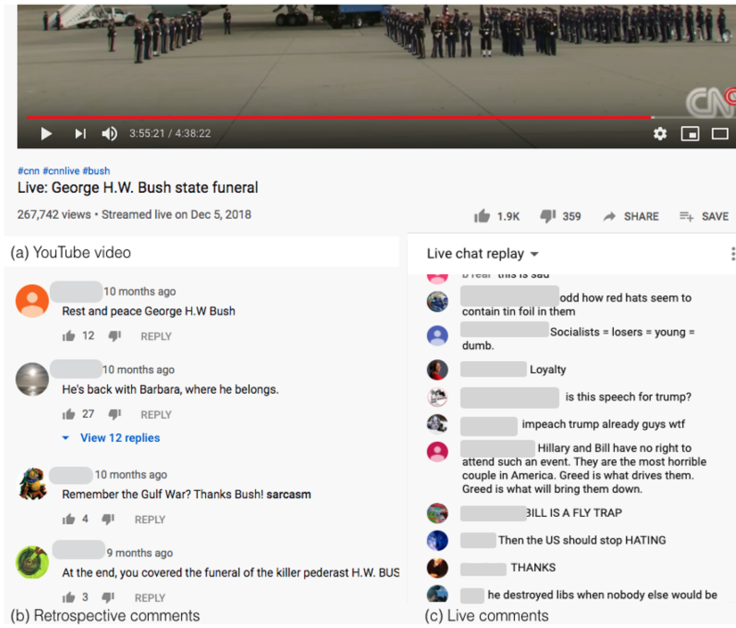

Fig. 1. Interface of the video (a), retrospective (b) and live comments (c) on YouTube.

excellent natural setting for which viewers' digital traces during (i.e., live comments) and after the live streaming (i.e., retrospective comments) can be compared.

2.1.2 News Media Events During Live Streaming. A rich prior literature on live streaming in human computer interaction has studied video streaming platforms like Twitch, with a particular focus on entertainment content such as gaming [42], life experiences [30, 31], and creative crafts [11]. These existing studies have revealed viewers' motives for watching live streamed content [31, 55], the formation of communities on these platforms [20], and the potential pitfalls of these platforms and the ways to moderate users' abusive behaviors [42].

The present study builds on this literature by examining the emotional dynamics of live broadcast media events on YouTube Live. Many news organizations post and stream their (live) video content through YouTube channels. Therefore, news events are an important type of content on YouTube Live relative to other streaming platforms such as Twitch. For example, ABC news first live streamed presidential debates between Obama and Romney in 2012 on YouTube [10], which started the practice of live streaming political debates. In addition to news, a particular media type on YouTube is media event, characterized by both ceremonial occasions such as ritual events (i.e., the Royal Wedding, sports games, mars landing) and shocking and traumatic occasions such as disruptive events (e.g., Notre-Dame fire, wars) [27].

2.2 Emotional Amplification during Live Streaming

Face-to-face interaction among multiple people during collective gatherings allow people to experience emotions together. A salient feature of emotions experienced together is an increased emotional intensity compared to the emotions experienced as an individual; we termed this increased emotional intensity "amplification." A large body of literature in affective science and social psychology has theorized why this amplification occurs. One account is the collective emotions perspective [16, 19, 53], which focuses on the roles that group identification and interactions with social others play on the experience of emotions. This perspective suggests that group identification and the influence of being exposed to multiple people's emotions (i.e., emotional dynamics) can lead to stronger emotional intensity [16]. A second account, shared attention theory (e.g., [43]), argues that a mental state of synchronous co-attention with others can amplify people's emotional responses to a stimuli relative to attending alone [45].

Consistent with both of these perspectives, traditional co-viewing, such as watching TV programs with family and friends in-person, is a more cheerful experience compared to watching alone [6]. Similarly, people used affect words more frequently and reported higher emotional arousal during mediated co-viewing, such as through dual-screening a media event (e.g., social media engagement during live broadcast [7, 49]). Live streaming platforms such as YouTube Live provides easy access to both live broadcast media and synchronous co-viewers and collapses them into a single screen. It is therefore reasonable to propose that amplification of emotional intensity should occur on live streaming platforms as well.

To examine this prediction in the context of YouTube Live, we evaluated emotions expressed by the audience in the comments posted during or after the live streaming took place. Since we focus on the change of magnitude of emotional intensity during live streaming, we follow prior work on collective emotions and shared attention (e.g., [16, 45]) to examine a single dimension of emotional intensity (or extremity, strength) rather than other dimensions, although emotion can be conceptualized as a multi-dimensional concept (e.g., the circumplex model, [41]). Emotional intensity refers to how an individual construes the relevant stimuli, which we argue will depend on whether others are present and sharing the emotional experience.

We analyzed the emotional properties of the language posted in the live and retrospective comments. To quantify emotional intensity, we used an imputation-based dictionary called Evaluative Lexicon [38, 40] and assigned a numeric emotional intensity value to each word in the live and retrospective comments. We examine positive and negative valenced emotional terms separately given that they are independent dimensions of emotion [8]. For example, the term "fantastic" (i.e., 4.07 out of 4.5) is rated higher in intensity than the term "valuable" (i.e., 3.18 out of 4.5) for positive valence. Since people's reactions to the media may manifest through their language usage in live comments versus retrospective comments, we expect live comments (e.g., "YOU ARE SO AWESOME!!!!!!!!!!!") to score higher in emotional intensity than retrospective comments (e.g., "Thank you my president"). [1]

H1-Amplification Hypothesis. *Live comments will be stronger in emotional intensity for both positive and negative emotions than retrospective comments.*

Since people's emotional responses to media and news events can vary depending on the content and valence of the event, we also asked,

RQ. *Will the amplification hypothesis be supported across event types?*

2.3 Temporal Dynamics and Potential Mechanisms

Given an overall increase in emotional intensity for live versus retrospective comments, how does any amplification effect emerge over time and what are the potential mechanisms? Two prominent frameworks suggest different accounts.

[1]Note that both the live and retrospective comments refer to the exact same video content in the YouTube interface.

2.3.1 Collective Emotions Perspective. The collective emotions perspective emphasizes the influence of others' emotions and predicts a continuous amplification over time. This increased intensification is assumed to occur through processes such as emotional contagion, through which observation of others' attitudes, emotions, and opinions can affect these states in oneself [3, 16, 21, 28, 56]. During live streaming, people observe and respond to others' comments in real-time, and thus are likely influenced or motivated to communicate with others and to express even stronger emotions (e.g., emotional contagion; [1]).

In contrast, when people experience media individually, such as watching the recorded event after the live streaming, emotional reactions tend to decay or fade away over time [16]. Therefore, collective emotions theory predicts an increase in emotional intensity for live comments over time, but decay in emotional intensity during retrospective comments, which should lead to an increasing gap in emotional intensity between live and retrospective comments over time. In particular, there should be no difference between live and retrospective initially, but the amplification effect should increase over time.

H2-Collective Emotion Hypothesis. *(a) Emotional intensity will increase over time in live comments, (b) but will decrease over time in retrospective comments.*

Under the collective emotions framework, group identification - individuals' self-categorization as a member of a group - plays a key role in collective emotions [17]. Thus, a possible mechanism behind amplification could be group identification; experiencing media with others together may trigger a sense of group belonging, which in turn, intensify the collective emotions. The level of group identification often manifests in the use of personal pronouns. First-person plural pronouns like "we" words could indicate a shared identity and affiliative motivation[47], whereas first-person singular pronouns like "I" words could indicate a sense of "I-mode", an individualistic orientation and self-focus of attention [51]. In an observational study examining broadcast live events (i.e., an episode of a TV show, a sports game), Sogut and colleagues (2015)[49] found that tweets posted during the live events used more first-person plural words and fewer first-person singular words than those posted after the events.

Moreover, it is important to note that group identification can manifest toward in-group or out-group members. Psychology theories suggest that people have both the tendencies to "bask in reflected glory" (BIRG;[4]) and to "cut off reflected failure" (CORF; [48]). To maintain a positive public image, people tend to claim a close connection with successful others by using more "we" words to describe the success [4], yet keep social distance from unsuccessful others using more "they" words to refer to "out-group" members. Collective emotions during live streaming may drive both in-group and out-group identification. In line with this rationale, the use of pronouns in live versus retrospective comments should take different forms in ritual (e.g., sports, the Royal Wedding) and disruptive (e.g., crime, terrorism) events. Therefore, we hypothesized that,

H2. *(c) Live comments will include more first-person plural pronouns (i.e., "We" category in LIWC) but fewer first-person singular pronouns (i.e., "I" category in LIWC) than retrospective comments for ritual events.*

H2. *(d) Live comments will include more third-person plural pronouns (i.e., "They" category in LIWC) but fewer first-person singular pronouns than retrospective comments for disruptive events.*

2.3.2 Shared Attention Theory. Unlike the collective emotions perspective, shared attention theory describes a static process that does not assume temporal dynamics. It also contrasts with the collective emotions perspective in terms of the necessity of emotional interactions. Specifically, shared attention theory argues that a mental state of synchronous co-attention is sufficient to lead to amplification of affect even without interpersonal communication or emotional interactions[43, 45]. That is, exposure to emotional expression by co-viewers is unnecessary to observe the amplification effect. Therefore, the shared attention account predicts that the amplification effect will occur at the beginning of live streaming. Specifically,

H3 - Shared Attention Hypothesis. *(a) Emotional intensity will be higher in live than in retrospective comments at Time 1.*

A prominent mechanism, according to shared attention theory, is a deeper level of elaborative processing of the experienced stimuli [43]. That is, the state of “we are attending to X” can elicit a stronger feeling of absorption in the shared experience [2], heightening emotional intensity. Lab experiments have consistently shown that shared attention can intensity people’s emotional reactions to stimuli through eliciting more thoughts about the stimuli content [45, 46].

How might language use in people’s emotional responses in live streaming reflect perceptual absorption? One way is through the emotional versus cognitive basis of attitudes suggested by words. Attitudes have been theorized to not only differ in valence but also in the extent to which the attitude is based on emotion versus cognition, or what is referred to as emotionality [12]. For example, the attitude conveyed by terms such as “wonderful”, "amazing", and "delightful" is more emotional than the attitude expressed by “helpful”, "outstanding", and "beneficial" [39]. Emotion-based terms have been shown to be more accessible in memory thus more likely to direct attention than cognitively-based terms [12]. Therefore, the perceptual absorption mechanism of emotional amplification would predict that attitudes in live comments will be based more on emotion compared to retrospective comments, with words scoring higher on emotionality appearing more often in live comments. For example, a live comment on a video about the Wedding of Prince Harry and Meghan Markle was “The wedding is marvelous and incredible. It’s simply wonderful;” a retrospective comment on the same video was "Congrats to the royal family from America."

In addition, recent research suggests that highly emotional words are more likely to occur with perceptual verbs such as “feel” while less emotional terms are more associated with cognitive verbs such as “believe” [38]. This distinction of verb use should also manifest in people’s reactions to the media, with more use of perceptual terms but less use of cognitive terms in live than retrospective comments. Prior work provides some support for the perceptual absorption hypothesis. For example, the ability to provide feelings of immersion (e.g., “being there”) and immediacy (e.g., “it is happening now”) of live streaming increased viewers’ engagement of the video [18]. Enhanced immersion and immediacy for co-viewing a live streamed event suggest that live streaming may trigger perceptual absorption as people process media. Therefore, more emotional and perceptual terms (e.g., feel, hear, see) are expected in live than in retrospective comments.

H3. *(b) Live comments will be more emotional for both positive and negative emotions, and (c) will use more words associated with perceptual processes than retrospective comments.*

3 METHOD

We compiled a dataset of YouTube live streamed videos posted in the last two years by popular English-speaking media outlets that included both live and retrospective comments on the exact same video content [24]. The dataset is publicly available on Open Science Framework (OSF). [2] Our resulting dataset included a total of 344 live stream videos that were collected from over 11 YouTube channels run by media outlets. We analyzed this corpus using multiple dictionaries to measure the emotional dimensions of individuals’ evaluations of the videos in our dataset.

[2]The dataset is available at https://osf.io/kre9z/?view_only=bba6fb87c57446dc94aba4f8bc7dc2ad

Type	Example	Valence	N videos	N comments	
				Live	Retro
Ritual	The Royal Wedding, Bush's funeral	Positive, negative	78	184,673	11,086
Disruptive	Notre-Dame de Paris fire, Hurricane Florence	Negative	32	72,778	7,181
General	Political debates, public hearing	Neutral	221	336,805	57,855

Table 1. Descriptions of live broadcast media event types

3.1 Data Collection

We identified a total of 363 live streamed videos that were posted by popular media outlets (i.e., ABC, BBC, Breitbart, Buzzfeed, CNN, Bloomberg, CBC, Daily, Euro news, Fox News, Fox Business, Time, USA Today, and the Washington Post) in the past two years. Given our focus on media and news events that have the potential to foster shared attention [5], we removed those about interviews and commercials. Spammers (e.g., "Subscribe") and irrelevant meta-data (e.g., "commendMetadata") were removed from the dataset, leaving us 331 videos.

This sample of live streamed videos could be broadly categorized into three groups: ritual, disruptive, and general news events. Drawing on media event theory [5], ritual events include coverages such as coronation (e.g., the Royal Wedding, Bush's funeral), contest (e.g., sports game, political debates), and conquest (e.g., mars landing; great steps for mankind) whereas disruptive events feature coverages on coerations (e.g., political protests, crime, violence), disasters (e.g., Notre-Dame de Paris fire, Hurricane Florence), and wars. General news events include regular journalism practices, such as press conferences, rallies and campaigns, and political hearings and briefings (see Table 1 for descriptions). Two research assistants independently coded the type of videos and reached acceptable intercoder reliabilities.

We developed a scraper that automatically collected both live and retrospective comments. Following common practice, our scraper was given a user-agent string and was programmed to take a break for approximately half a minute after each request was made in order to resemble a human user, and to lessen the burden on YouTube's servers with requests [32]. It is important to note that given the amount of traffic YouTube's server experiences, it is highly unlikely that our scraper negatively affected YouTube's server or other users of the service. All our data collection took place from June 30 to July 7, 2019. Overall, the average word count (WC) for live comments (n = 7.88) was one-third of the WC for retrospective comments (n = 24.57), which may be an artifact of the strict character limits (200) imposed for the live comments.

3.2 Data Analysis Using Imputation-Based Dictionary

We employed the lexicon/dictionary approach for data analysis. People's usage of words in their daily lives has been extensively studied for its expressive power to describe their beliefs, personalities, and emotions [33]. The lexicon/dictionary approach is to classify a text into different categories based on an existing wordlist. Common dictionaries that have been validated across different contexts include but are not limited to Linguistic Inquiry and Word Count [34], Valence Aware Dictionary and sEntiment Reasoner [23], and Evaluative Lexicon 2.0 [40].

3.2.1 Evaluative Lexicon 2.0. In this study, we used EL 2.0, an imputation-based dictionary for measuring "emotionality, extremity, and valence" in textual data, to analyze intensity and emotionality of YouTube comments [38, 40]. We chose to use EL dictionary for three reasons. First, it provides a more accurate indicator of measuring the intensity of evaluation by avoiding confounding the frequency of emotional words and the intensity of emotions. Second, it provides a more accurate judgment about texts with no emotion by assigning no value instead of zero (see for a review[40]). Last, it treats emotionality as a distinct construct from intensity and provides measures of both intensity and emotionality of a single word. For example, both terms "amazing" and "wonderful" imply the same level of intensity (4.00 in EL), but different levels of emotionality ("amazing" is 6.98 and "wonderful" is 5.92) [39]. EL 2.0 compares word occurrences against a wordlist. The wordlist includes 1,541 adjectives associated with individuals' evaluations across a wide range of topics, for which the ratings of emotionality and valence are numerically represented.

Both emotionality and valence ratings of words are based on human ratings where emotionality is rated by the extent to which the word is perceived to be based on emotion versus cognition (0 = not at all emotional to 9 = very emotional) and valence is rated by the perceived intensity of positive or negative emotions (0 = very negative to 9 = very positive). Following the calculation procedure outlined in Rocklage et al., (2018) we obtained the weighted average scores of emotionality and intensity for both positive and negative valence for each comment. EL 2.0 has been used in a wide range of textual data, from product reviews on Amazon.com [38] to tweets about Olympic gold medalists [29]. However, it has not been applied and validated in evaluations of YouTube videos. The trade-off between accuracy and coverage should be noted [39]. In our data, EL 2.0 covers 20.74% of live comments, and 44.19% of retrospective comments. To ensure the internal validity of the EL dictionary, we conducted validation studies using VADER and LIWC.

3.2.2 Validation using VADER and LIWC. To validate the results using EL 2.0, we used other linguistic tools, VADER and LIWC, to examine the language differences between live and retrospective comments. VADER is appropriate for short social media text, taking account of sentiment-laden slang words and emojis as indicators of emotions [23]. VADER also assigns numeric values to words associated with positive and negative emotions (from -1 = very negative to 1 = very positive and 0 = neutral or neither). In this case, compared to EL 2.0, VADER does not distinguish neutral emotion from the absence of emotional words nor includes the emotionality dimension. LIWC is one of the most common dictionaries in the social sciences. It contains a large wordlist (N = 5,690), and the number of affective words (i.e., positive and negative emotions) is also large (N = 1393). Unlike EL 2.0 or VADER, LIWC follows a frequency-based dictionary approach, counting the presence or absence of words to measure the constructs of interest. LIWC treats all emotional words the same level of emotionality and intensity, and assumes the greater frequency the word the more intense the construct is.

3.3 Data Analysis Approach

For hypothesis testings, different modeling methods were used to examine how linguistic dimensions (i.e., intensity, emotionality, exclamation marks, frequencies of cognitive, perceptual words and pronouns) differ across comment status (live vs. retrospective). Since VADER assigns zero to both non-emotional and neutral comments, a majority of comments contained zero for intensity measures. Due to excess amount of zeros, we used the hurdle model to treat zeros and non-zeros for intensity as two separate processes [57]. We first fitted a logistic regression to predict the probability of observing a non-zero value and then a Gamma GLM with a log link to predict the mean of the non-zero data of retrospective relative to live comments.

When using ratings of LIWC, we performed a corpus analysis by aggregating live and retrospective comments for all videos into two separate corpora, regardless of the videos they were posted about. Given that the average WC in retrospective comments was larger than the WC in live comments, and that positive [$r(674740) = .54$, $p <.001$] and negative emotions [$r(674740) = .44$, $p <.001$] were positively associated with WC, WC may bias the results of frequency of affective words if taking the by-comment approach. To avoid the potential confounding of WC, we took a corpus analytic approach to compare the frequency of words in the two corpora (live vs. retrospective comments) based on a log-likelihood ratio test (LLR) [35]. The LLR quantifies the extent to which the observed difference of word occurrence between two corpora is likely to occur. A conservative significance level ($p <.001$) was used to adjust for multiple comparisons [36].

Hypotheses about temporal dynamics (i.e., H2ab, and H3a) are contingent upon the likelihood that people have been exposed to the preceding comments. Comments in live streaming are ordered chronologically by default, and thus people who posted a comment later may have been exposed to the preceding comment. Retrospective comments, in contrast, may not necessarily be ordered by time but determined by several factors, such as the streamers' preference. High frequency of likes may also make a comment stay on top. Since the ranking algorithm of comment is unavailable, we first examined the association between number of likes and the time order of a comment. In a negative binomial regression predicting the number of likes with order position, word count, and key language features, we found that the order position was positively associated with the number of likes ($B = .00$, $SE = .00$, $p <.001$). It indicated that the later a comment was posted, the more likes it may receive. We assumed therefore that the order position of a comment is largely consistent with the time order in retrospective comments.

It is important to note that we grouped comments in each video into five temporal quintiles based on their posted time (i.e. the first 20% of the comments were grouped as quintile 1, the second 20% as quintile 2, etc.).[3] We analyzed these temporal quintiles instead of raw timestamps since the number of comments, and thus the range of time order values, varied widely across videos.

4 RESULTS

4.1 H1 – Emotional Amplification Hypothesis

Are emotional responses to live streamed media more intense than to recorded media? We first fitted linear-mixed models to predict emotional intensity for positive and negative valence with the fixed effect of the comment status (live vs. retrospective) and random intercept effects for all videos and viewers. Our results supported H1 - amplification prediction: live comments scored higher in both positive ($B = .09$, $SE = .01$, $p < .001$) and negative emotional intensity ($B = .04$, $SE = .01$, $p < .001$) than retrospective comments, suggesting that live comments were more positively and negatively intense than retrospective comments. Additional analyses using VADER and LIWC validated the findings, and thus supported H1 (see Appendix for detailed results). Moreover, the emotional amplification effect was also observed for individuals ($N = 12{,}878$; 9.01%) who posted both live and retrospective comments (see Appendix), which indicated that individual differences do not seriously threaten the emotional amplification findings.

4.1.1 Emotional Amplification by Event Type: Did the amplification effect differ across media event types? We fitted linear-mixed models with event type and its interaction with comment status as fixed effects. For positive intensity, only the main effect of comment status was significant, F(1,

[3]The first comment posted for a video would be assigned order value 1, the second comment order value 2, etc. We used order instead of raw timestamp as the unit of analysis for two reasons: (1) timestamp varied widely by video and (2) the specific time that a comment was posted does not matter for our question as long as the relative chronological order of the comments was captured.

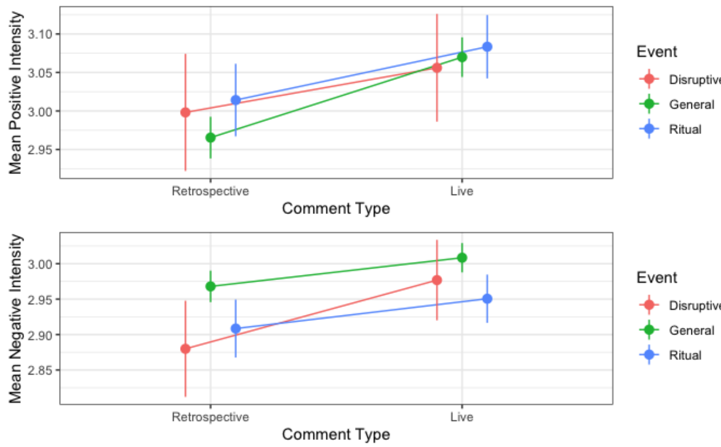

Fig. 2. Emotional intensity as a function of comment status and event type for positive and negative emotions.

34786) = 43.14, p <.001, with live (M = 3.07, SE = .01) greater than retrospective comments (M = 2.99, SE = .02). Neither the event type nor the interaction effect was significant (Fs < 2.34, ps >.10). For negative intensity, the main effect of comment status was significant [F(1, 19671) = 24.28, p <.001], again with live (M = 2.98, SE = .01) greater than retrospective comments (M = 2.92, SE = .01). The main effect of event type was also significant, F(2, 294) = 5.51, p <.01, with general news events (M = 2.99, SE = .03) significantly more negatively intense than ritual events (M = 2.93, SE = .02), t(282) = 2.95, p = .01; however, the interaction between comment status and event type was not significant [F(2, 23140) = 1.55, p = .21]. Thus, we concluded that the amplification effect of live streaming held across all event types (see Figure 1).

4.2 H2 - Collective Emotions Hypotheses

4.2.1 Temporal dynamics. To test whether emotional intensity increases over time in live comments as predicted in H2(a), but decreases over time in retrospective comments as predicted by H2(b), we first examined if the increase of emotional intensity differed by time. Linear mixed models predicting positive and negative intensity in live and retrospective comments with fixed effects of temporal quintile (random intercept of video and random slope of temporal quintile) showed that for live comments, neither positive (B = .00, SE = .00, p =.81) nor negative intensity (B = .00, SE = .00, p = .72) changed over time (Figure 3 circle points). Thus, the collective emotions prediction of increased emotional intensity over time in H2(a) was not supported. For retrospective comments, both positive (B = -.01, SE = .00, p = .01) and negative intensity (B = -.01, SE = .00, p =.04) decreased significantly over time (Figure 3 triangle points), supporting the prediction in H2(b) for decay in emotional expressions over time.

4.2.2 Group Identification Mechanism. We tested the group identification hypothesis as a mechanism for collective emotions theory. Were there more group-oriented versus individual-oriented pronouns in live than in retrospective comments? Our corpus analysis included first-person singular pronouns (e.g. "I") as individual-oriented and first-person plural (e.g. "we") and third-person plural (e.g. "they") as group-oriented pronouns. We also analyzed these pronoun patterns across the three event types. As shown in Table 2, the opposite pattern was observed. For all event types, group-oriented pronouns were observed more often in retrospective than in live comments.

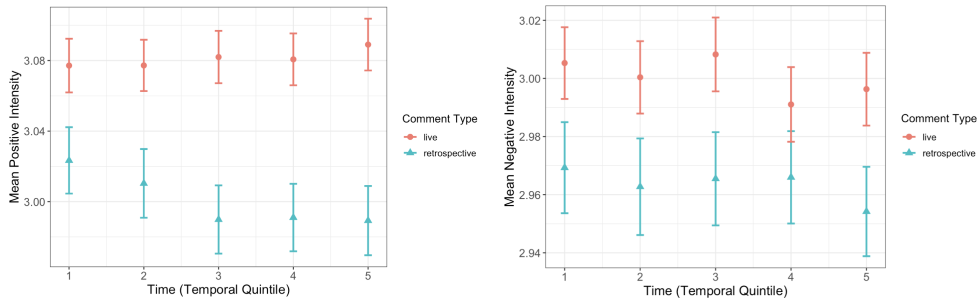

Fig. 3. Positive intensity (left figure) and negative intensity (right figure) by time between live and retrospective comments.

	First-person singular (e.g., I, me) %			First-person plural (e.g., we, ours) %			Third-person plural (e.g., they, them) %		
	Live	Retro	LLR	Live	Retro	LLR	Live	Retro	LLR
Ritual	1.60	1.68	9.46**	1.02	1.07	5.37*	1.19	1.46	132.55***
Disruptive	2.03	1.98	1.75	0.88	1.44	332.06***	1.16	1.69	236.50***
General	1.49	1.46	4.46*	1.27	1.40	116.84***	1.44	1.70	405.99***
Overall	1.55	1.53	2.88	1.13	1.35	548.48***	1.31	1.66	1238.20***

Table 2. Comparing Word Frequencies of Personal Pronouns Between Live and Retrospective Corpus. Word frequencies were obtained using LIWC. Log-likelihood ratio (LLR) equates 3.84 (5% level), 6.63 (1% level), 10.83 (0.1% level), and 15.13 (0.01% level).

Individual-oriented pronouns were not different overall, but when there was an effect it was in the opposite of the expected direction. Thus, the group identity mechanism predicted in H2(cd) was not supported.

4.3 H3 - Shared Attention Hypotheses

4.3.1 Temporal Dynamics. The shared attention hypothesis (H3a) posited that emotional intensity will be higher in live than in retrospective comments immediately (i.e., Time 1) because the amplification is not driven by exposure to others' emotions. Using t-tests (bonferroni corrected to $p < .01$), we found that across temporal quintiles, both positive emotional intensity (p's $< .001$) and negative emotional intensity ($p = .02$ for quintile 4; $ps < .01$ for all other quintiles) was higher in live comments than retrospective (see Figure 3). Therefore the overall emotional amplification effect in live comments observed in H1 was manifest immediately, consistent with the shared attention hypothesis (H3a).

4.3.2 Perceptual Absorption Mechanism. To test the perceptual absorption mechanism for the shared attention perspective, we examined two types of language. First, we examined the prediction that live comments would include more positive and emotional terms than retrospective comments [H3(b)]. Similar to the emotional intensity analysis, we fitted linear-mixed models to predict the emotionality (for both positive and negative emotions) with the fixed effect of the comment status (live vs. retrospective) and random intercept effects for videos. Results showed that the main effect

		Live		Retrospective		
		5,317,605		1,983,428		
Categories	**Examples**	**Frequency**	**%**	**Frequency**	**%**	**LLR**
Emotional						
Positive emotions	happy, pretty, good	209,012	3.93	75,930	3.83	38.96***
Negative emotions	hate, worthless, enemy	187,290	3.52	64,081	3.23	360.71***
Exclamation marks	!	196,014	3.69	60,182	3.03	1803.37***
Psychological						
Cognitive process	cause, know, ought	505,283	9.50	208,986	10.54	1556.08***
Perceptual process	see, touch, listen	131,445	2.47	44,916	2.26	260.54***

Table 3. Comparing Word Frequencies Between Live and Retrospective Corpus. Word frequencies were obtained using LIWC. Log-likelihood ratio (LLR) equates 3.84 (5% level), 6.63 (1% level), 10.83 (0.1% level), and 15.13 (0.01% level).

of comment status was only significant in positive [F(1, 30623 = 49.66, p <.001)] but not negative valence [F(1, 30530) = 3.49, p = .06]. Specifically, live comments were significantly more emotional for positive [t(30623) = 7.05, p <.001] than retrospective comments, suggesting that comments were more emotion-based in live than retrospective comments, but only for positive emotions, partially supporting H3(b). We also observed that these emotional dynamics depend on event type. The positive emotionality effect was significant for ritual and general news events (*ps* < .001; see Appendix for detailed results), while negative emotionality was observed only for disruptive events, regardless of the comment status [F (2, 327) = 8.41, p <.001]. This pattern is consistent with the characteristics of the different media events, with disruptive events depicting negative news (e.g., Notre Dame fire) relative to ritual (e.g., the Royal Wedding) or general news (e.g., press conference).

Finally, we examined the second perceptual absorption prediction that live comments would include more perceptual than cognitive terms relative to retrospective comments [H3(c)]. As shown in Table 3, live comments included significantly higher percentages of perceptual terms but lower rates of cognitive terms than retrospective comments. This pattern of language use is also consistent with the perceptual absorption hypothesis H3(c).

5 DISCUSSION

The affordances of live streaming platforms allow people to view media events in real time and experience it with others through live chat. Using real-world comments on a live streaming platform that were connected to a specific media news event, our research revealed an emotional amplification effect for comments during live streaming in which the intensity of comments was higher during live comments compared to retrospective comments. Our research suggests that this emotional amplification occurred across three different news types, and that the effect was largely driven by shared attention rather than exposure to others emotional expression.

The present research adds to the literature on live streaming by examining emotional dynamics on YouTube Live - a popular video sharing platform with substantial interest in news and media events. Our findings not only identify the amplification of emotional intensity at scale but also present initial evidence for the shared attention theory as an explanation for why the effect takes place. Lastly, this study introduces a novel dataset (available on OSF), with over 750,000 live and retrospective comments on 331 YouTube videos that have been classified into media event types, which presents rich data for future research to explore.

5.1 Amplified Emotions on YouTube Live

Consistent with Durkheim's general notion of "collective effervescence" that collective gathering can facilitate affect, our findings showed a consistent emotional amplification during live comments relative to retrospective comments, regardless of event types or temporal dimensions. That is, individuals demonstrate stronger emotional responses to a media event when they experienced it with others in real time compared to experiencing the exact same media individually. When people engaged with the media individually we found a consistent decay in intensity over time. This pattern of emotional decay in which emotional intensity decreases as the expression of the emotion occurs further in time from the stimulus is a well-replicated and well-understood phenomenon in psychology [16].

For people that experienced the media event through live streaming, their affect was higher than retrospective right away, suggesting that amplification is not driven by exposure to other commenters' emotional expressions, as predicted by collective emotions theory. Instead, the observation that emotional amplification was immediate and sustained relative to the emotional decay observed for people experiencing it alone suggests that our data are more aligned with shared attention theory [43]. Our findings also contribute to the ongoing debate on the boundary conditions for emotional amplification [16, 25]. A minimalistic shared viewing experience appears to be sufficient to trigger an amplified experience [45].

The affordances of YouTube Live are also likely to play a role in the emotional amplification effect, although we were unable to directly test or compare these in our field study. For example, prior work has shown that the ephemeral nature of IRC in online discussions can cause information overload such that people have difficulty processing others' comments [20, 26]. Therefore, the massive and fast flow of live chats may have less emotional influence, which may have undermined the operation of collective emotion dynamics. Instead, the ephemeral nature of the live chats may have facilitated shared attention by emphasizing social presence of others and enhancing participants' perceptual absorption in the media and comments. In addition, the ephemerality of IRC may also elicit emotional amplification by reducing commenters' self-presentational concerns. People may expect their comments, especially with pseudonymous usernames on YouTube, to be less noticed, read, or judged by others, which may also have led to more extreme sentiment. Future work will be required to understand how affordances such as ephemerality and pseudonymity play a role in the emotional amplification effect.

5.2 Collective Emotions and Shared Attention Mechanisms

We hypothesized two potential mechanisms for emotional amplification. Contrary to the group identification hypothesis predicted by the collective emotions theory (e.g., [49]), viewers' emotional responses were more individual-level focused in live than retrospective comments. It suggests that experiencing emotions with others during live streaming may fail to evoke a "we-mode" in ritual events or "they-mode" in disruptive events, but instead reinforces personal feelings and engagement with the live broadcast media event. As noted above, the fast flow of live chat messages may be difficult to process and thus less likely to elicit the feelings of connection or group identification. Moreover, ritual and disruptive media events are not necessarily group identity-based (to the same extent as events such as competitive group sports). Thus, these events could be less likely to trigger collective orientation with a group. In addition, even for group identity-based media events, viewers who identify with different groups may use group-specific language (such as inside jokes, etc) to maintain appropriate social distance with co-viewers, leading to non-significant findings when only considering personal pronouns.

Under the shared attention framework, however, we observed that emotional amplification may be related to a greater level of perceptual absorption, as indicated by comments based more on emotions than cognition during live streaming. The YouTube Live interface involves salient cues (e.g., "X watching now", "streamed X min") that serve to increase the feeling of "being there" and "being one of the first" when people engage in live events [18]. Therefore, as predicted, the experience of attending simultaneously with others during live streaming may trigger deeper encoding of positive emotions for ritual and general news events, and amplify their emotional experience. However, people's reactions to disruptive events are constantly emotion-based rather than cognition-based, compared to the other events, suggesting a powerful effect of event type over comment status.

5.3 Implications for Live Streaming Platforms

There are several important implications for these findings for the platforms that offer live streaming services. An increasingly crucial issue for social media platforms, for instance, is content moderation [37], and the emotional dynamics that moderators experience [55]. The emotion findings we observe here can provide some insight for these platforms on how they may wish to manage content moderators for live streamed and archived media events. For example, given a finite amount of content that can be moderated at any given time, our research findings suggest that live streaming content will need heightened attention towards moderation as it is likely to provoke intensified emotional reactions. Also, because the emotional amplification effect appears to take place immediately, content moderators should be in place at the start of live streamed media. Indeed, other research examining Twitch found that, enabling chat moderation during live streaming may deter highly intense negative emotions [42]. Our emotional decay findings, in contrast, suggest that moderation of retrospective comments may become less urgent over time. Further, our data also suggest that disruptive media events, such as natural disasters, involve comments with particularly high levels of negative emotionality, which could be useful in alerting moderators to be particularly cognizant of harmful or problematic comments during live streamed disruptive events.

A second and related issue is that content moderators that are asked to moderate live events may be subject to the emotional amplification effect themselves. With the increasing concern regarding moderators' psychological health [15] it is important to understand under what circumstances moderators may be most at risk for psychological harm [55]. Our findings suggest that moderators asked to moderate live streaming content may experience intensified emotions. The shared attention perspective and our supporting data suggest that if they are attending the same live streamed media as the commenters, they may also be subject to more intense emotions. Being aware of this phenomenon, and the perceptual absorption mechanism by which it operates, may help platforms ameliorate the emotion amplification effect for moderators by designing moderation platforms to interrupt the emotional amplification effect, or to help moderators deal with these intensified emotions in debriefing or when providing well-being interventions.

5.4 Limitations and Future Directions

Since the current study used field data, it is difficult to make causal claims about whether live streaming leads to emotional amplification. For the same reason, the explanations of why more extreme emotions occurred in live streaming (i.e., greater perceptual absorption in the event) are weak in causal interpretation. It is likely that shared attention is not the only cause of amplification. Since live streaming platforms naturally confound the temporal status of a video (live vs. retrospective) and the presence of others, field data cannot definitively distinguish between the two potential causes. Future work should conduct randomized control trials to further examine whether live (vs. recorded) video and/or co-viewing (vs. solo-viewing) increases people's affective reactions to media events. The second limitation in relation to the observational data concerns the selection bias in the sample. It is likely that people who commented on the live video were already emotive about the events. Approximately 90% of users in our dataset only posted either live or retrospective comments rather than both, making it hard to statistically tease apart the impact of individual differences on amplification. Nonetheless, we were able to examine individuals who posted comments to both live and retrospective videos and found that the emotional amplification effect still held for these individuals, suggesting that our results were not entirely due to selection bias.

Moreover, we examined emotional dynamics of collective emotions by investigating the change of emotional intensity over time for live and retrospective comments, respectively. While this approach can reveal when amplification occurs across temporal quintiles, it may lose nuanced insights into the specific processes such as contagion or imitation and deterrence in IRC [42]. Advanced statistical modeling is encouraged for future research, such as agent-based modeling and interrupted time-series models, to measure the emergence of collective emotions during live streaming and to examine the impacts of live streamed media events on collective emotions [13, 14].

As in most text analysis, our research using EL and LIWC did not capture uncommon language, especially unique expressions in IRC (e.g., slang, memes, and acronym). Future work should develop advanced dictionaries that are more suitable for analyzing short text in live chat system. Lastly, it is important to note that our findings based on live broadcast media events on YouTube may suffer external validity. Findings may not be generalized to other live streaming platforms such as Twich.tv and Facebook Live, due to different audience characteristics and different affordances. For example, the pseudonymity affordance may moderate the emotional amplification. Compared to YouTube Live, Facebook Live often allows viewers' comments to be attached with their real names, which may encourage less extreme emotions because their comments are more likely to be identified and judged by others. Some unique features on the interface of YouTube may also strengthen the amplification effect. For example, due to the lack of the "like" buttons on live chat, users might express their resonance with previous comments by repeating them, which could reinforce the intensity of emotions. The ability to "like" previous comments in retrospective comments may mitigate emotional intensity, as indicated by the constant intensity decay over time in almost all event types in our data. Whether the emotional amplification can be observed in other live streaming platforms with unique affordances deserve future research.

6 CONCLUSION

Live streaming fosters co-presence and social interaction in everyday viewing practices, creating a mediated co-viewing experience. Our work, using an observational analysis of large-scale text data, reveals that emotions experienced together with others during live streaming are more intense than emotions experienced individually after the live streaming. This emotional amplification effect is consistent across media events and time points. This effect is best explained by perceptual absorption as people process live media as predicted by shared attention theory. Our findings reveal emotional dynamics during and after live streaming, and highlight the urgency of further improving the live streaming platforms to strategically perform content moderation and improve the well-being for moderators. As the pandemic of COVID-19, which began in early 2020, and the practice of social distancing has made clear, understanding the emotional dynamics of live streaming as a practice for staying connected via technology is increasingly important.

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A VALIDATION FOR H1: AMPLIFICATION HYPOTHESIS

Using intensity ratings of VADER to validate the above results, we found that retrospective comments were 73% more likely to observe a non-zero positive emotion score, but given a non-zero score, the positive emotion value was higher for live than retrospective comments, *Exp(B)* = .69, *SE* = .03, p <.001, 95% *CI* [.68, .69]. These data suggested that although live comments may be more likely to include non-emotional words, possibly due to lower word count, live comments were more positively intense than retrospective comments when emotional terms were present. Similarly, when emotional terms were present, live comments were more negatively intense than retrospective comments, *Exp(B)* = .63, *SE* = .00, p <.001, 95% *CI* [.631, .639]. Thus, the validation analysis supported H1.

We also validated the results using LIWC. As shown in Table 1, live comments featured significantly higher percentages of positive (*LLR* = 38.96) and negative emotions (*LLR* = 360.71), and exclamation marks (*LLR* = 1803.37) than retrospective comments. This set of validation analyses suggested that people's aggregate reactions to a video tend to be more intense when the video was live streaming than when it had been archived, which was consistent with the EL and the VADER results.

B INDIVIDUAL DIFFERENCES

To examine whether the amplification is driven by individual differences, we filtered for viewers who have commented on both live streamed and recorded videos to formally compare the emotional intensities between the live and retrospective comments posted only by the subset of for individuals who posted in both. Linear-mixed models were performed to predict positive and negative emotional intensity and emotionality, with comment status as a fixed effect and random intercepts of viewer and video. The main effect of comment status was still significant across all the models (*ps* < .05), which provides some evidence that the effect was not purely driven by selection bias (i.e. that individuals who are high in emotional intensity post in live comments vs. retrospective comments).

C RESULTS FOR H3(B)

Results showed that, for positivity, the main effect of comment status was significant [$F(1, 30623) = 49.66$, $p < .001$], whereas the main effect of event type was not [$F(2, 343) = 1.74$, $p = .17$]. The main effect of comment status was qualified with an interaction effect between comment and event type [$F(2, 31578) = 8.22$, $p < .01$]. A post-hoc contrast showed that live comment was significantly more emotional than retrospective comments for ritual [$t(50323) = 14.42$, $p < .001$] and general news events [$t(28889) = 4.02$, $p < .001$] but not for disruptive event [$t(29673) = 1.43$, $p = .15$]. For negativity, only the main effect of event type was significant [$F(2, 327) = 8.42$, $p < .001$]. Disruptive event was more negatively emotional ($M = 5.12$, $SE = .06$) than ritual ($M = 4.94$, $SE = .04$) [$t(336) = 2.78$, $p = .02$] or general news events ($M = 4.88$, $SE = .02$)[$t(339) = 4.04$, $p < .001$].

Received October 2019; revised January 2020; accepted March 2020