Emotion analysis of user reactions to online news

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Abstract

Purpose – Social media allow for observing different aspects of human behaviour, in particular, those that can be evaluated from explicit user expressions. Based on a data set of posts with user opinions collected from social media, this paper aims to show an insight into how the readers of different news portals react to online content. The focus is on users' emotions about the content, so the findings of the analysis provide a further understanding of how marketers should structure and deliver communication content such that it promotes positive engagement behaviour.

Design/methodology/approach – More than 5.5 million user comments to posted messages from 15 worldwide popular news portals were collected and analysed, where each post was evaluated based on a set of variables that represent either structural (e.g. embedded in intra- or inter-message structure) or behavioural (e.g. exhibiting a certain behavioural pattern that appeared in response to a posted message) component of expressions. The conclusions are based on a set of regression models and exploratory factor analysis.

Findings – The findings show and theorise the influence of social media content on emotional user engagement. This provides a more comprehensive understanding of the engagement attributed to social media content and, consequently, could be a better predictor of future behaviour.

Originality/value – This paper provides original data analysis of user comments and emotional reactions that appeared on social media news websites in 2018.

Keywords Social media, Opinion mining, User comments, Online news, User reactions

Paper type Research paper

1. Introduction

The interactive properties of social media have transformed users from passive observers to active participants, which provided a significant amount of social and network value to both users and organisations through social media, as users comment, review and share information online (Dolan *et al.*, 2015). To make a better understanding of the utility of this type of information, it is necessary to unveil a hidden relationship between content pages on social media and their users. One of the most significant latent variables that exist in this relationship is emotion. Over the decades, researchers were trying to understand how and why emotions appear and disappear, and how we can influence various communication processes. People always influence others' decisions in their daily interactions in different ways. One way of influence is via emotion transfer (e.g. word-of-a-mouth) which overwhelms social media (Khobzi *et al.*, 2019). Nowadays many people share almost every moment of their lives online, ranging from their opinions, sentiments and views to multimedia content such as personal photographs or home videos (Kümpel *et al.*, 2015). The massive user-generated content, commonly known as big data, attracts researchers to investigate what causes such behaviour, and how to use the acquired knowledge to the best benefit. And the essence of it is an emotion, which stimulates the behaviour.

Emotions are a part of our internal activity (Plutchik, 1962) and execute a crucial role in decision-making and cognitive relation processes (Shen *et al.*, 2017). Moreover, Kramer *et al.* (2014) confirmed that emotional contagion is possible via text-only communication and that emotions flow through social media. Therefore, the focus of this study is put on certain aspects of emotion mining as seen from the social media perspective. This study provides an insight into the user reactions to online news on Facebook, a social media service that is increasingly engaged for purposes of news distribution (Al-Rawi, 2017). The focus of this study is placed on assessing users' activities on the Facebook pages of 15 world-class newspapers, i.e. on user comments to posted messages, their *likes* and *shares* as well as their emotional reactions provided by emojis (*Angry*, *Haha*, *Love*, *Sad* and *Wow*). More specifically, the relationship between the emotions from the text (e.g. posted messages and comments to these) and the emotional reactions of users is investigated in detail. While there are numerous studies that investigate social media activities and

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emotions (Tzacheva *et al.*, 2019), especially in the area of predicting emotions and reactions using various machine and deep learning models (Clos *et al.*, 2017; Krebs *et al.*, 2018) and analysing emotional reactions to particular content or topic (Al-Zaman and Ahona, 2022), most of these models leave the semantics of words in word embeddings and emotional values in the reaction distributions, without more in-depth analysis of the relations between different kinds of emotion. There is less research on the connection between different kinds of emotion from text and emotional reactions to it. This study aims at fulfilling this gap by exploring emotional value from text based on eight emotions upon which the emotion lexicon was built (Mohammad and Turney, 2013), namely, *Anticipation, Anger, Fear, Disgust, Joy, Trust, Sadness* and *Surprise* (Ekman, 1992) as well as valences *Positive* and *Negative,* and its relationship to the emotional reactions of people on social media. The findings are based on multiple regression models and factor analysis that confirmed correlations between certain emotions from text and reactions to it.

2. Related work

2.1 Emotion mining

Emotions are considered a key semantic component of human communication (Banerjee and Dutta, 2015). Scherer (2000) defines emotion as a "relatively brief episode of response to the evaluation of an external or internal event as being of major significance". There are two widely held families of theories of emotion (Jurafsky and Martin, 2015). In one family, emotions are viewed as fixed atomic units, limited in number, and from which other emotions are generated, often called *basic* emotions (Tomkins, 1962; Plutchik, 1962). One of the representatives of this family is Ekman (1992), who showed that humans experience six cross-cultural, universal emotions, recognized by universal facial expressions, namely, *anger, disgust, fear, joy, sadness* and *surprise*. The second class of emotion theories views emotion as a *multi-dimensional space*. For instance, Russell's (1980) circumplex model maps emotions on a three-dimensional space, namely, *valence, arousal* and *dominance*, where valence defines the pleasantness of the stimulus, arousal defines the intensity of emotion provoked by the stimulus and dominance determines the degree of control exerted by the stimulus. However, none of the emotion models is better than the others, because all models have advantages and disadvantages. The selection of an emotion model depends on the set of emotions that we want to detect (Canales and Martinez-Barco, 2014).

Over the past decade, there has been a large amount of work with different approaches to detecting emotion from the text (Acheampong *et al.*, 2020; Murthy and Anil Kumar, 2021). Many statistical and machine learning classifier techniques have been developed for affective computing (Banerjee and Dutta, 2015), applicable to both coarse-grained (positive or negative) and fine-grained emotion classification (different levels of positive and negative). Emotion detection techniques can be divided into lexicon-based approaches and machine learning approaches (Canales and Martinez-Barco, 2014). Lexicon-based approaches rely on lexical resources such as lexicons, bags of words or ontologies, while machine learning approaches apply algorithms based on linguistic features (Tripathi *et al.*, 2016). A lexicon-based way to analyse the sentiment (or emotion) of a text is to consider the text as a combination of its words. The sentimental or emotional value of the whole text can be defined as the sum of the sentiments (or emotions) of the individual words (Silge and Robinson, 2018).

As a consequence of advancing the field of emotion mining due to huge amounts of available data, there is a growing number of studies that explore the relationship between emotion and engagement on social media (Luarn *et al.*, 2015; Sandoval-Almazan and Valle-Cruz, 2020). Tian *et al.* (2017) demonstrated that Facebook reactions and comments are a good data source for investigating indicators of user emotional attitudes. A recent study on engagement in emotional news on Facebook (Choi *et al.*, 2020) used regression models to investigate the relationship between sharing, commenting and reacting to emotional news content that was evaluated using software tools. They found that "people are less likely to share or comment on news stories that convey positive emotions, whereas they tend to react to positive news frequently" and that "sadness is the most noticeable emotion in attracting users' engagement". Here, the granularity of Facebook emotional reactions was not analysed, i.e. the reactions were taken as one variable referring to *likes*, *angry*, *haha*, *love*, *sad* and *wow* emojis. Another study (Aldous *et al.*, 2021) introduced time dimension into emotion research by measuring nine emotions (anger, anticipation, anxiety, disgust, joy, fear, sadness, surprise and trust) and two sentiments (positive and negative) to predict emotional audience reactions before and after publishing the posts. Findings show "significant differences for positive emotions but not for negative in the comments among the platforms" implying that news outlets have leverage in steering emotional engagement for posts on social media platforms.

Trying to study more deeply the connection between different emotions, this paper uses a lexicon-based approach (Avdić and Bagić Babac, 2021) for analysing the news posts and comments on Facebook to measure the amount of various positive and negative emotions encoded in the content. Combining the emotions from text with other variables related to user reactions and posts, this study aims to answer the following research questions:

RQ1. What kind of emotions have appeared in news content on social media?

RQ2. What kind of user reactions and comments have appeared in response to the news content?

RQ3. What is the relationship between the observed news content and user reactions/comments?

In answer to these questions, we use a data set of more than 5.5 million posts and user comments from 15 worldwide popular news portals on Facebook and draw conclusions based on the following theoretical framework.

2.2 Theoretical framework

We build our conceptual framework on Katz's Uses and Gratifications Theory (UGT) (Katz and Lazarsfeld, 1955), as it is an approach to understanding *why* and *how* people actively seek out specific media to satisfy specific needs. Moreover, it is an audience-centred approach to understanding mass communication (Severin and Tankard, 1997), which proposes that the public seeks information and specific communications sources to fulfil satisfaction while expanding their knowledge and social engagements through specific media outlets (Katz *et al.*, 1973). To this end, UGT considers individuals as conscious of their consumption, and also that media competes for gratification with other sources (Katz *et al.*, 1974).

UGT has especially been used within research on online contexts, including online games, Facebook and Twitter (Hamari and Sjöblom, 2017). The application of UGT to examine the influence of social media content on engagement behaviours recognises the interactive nature of the media and extends the use of the theory (Dolan *et al.*, 2016). A recent study of the UGT in the context of social media usage (Leung, 2013) has found that users have specific motivations, namely, social motives and affection, the need to vent negative feelings, recognition, entertainment and cognitive needs. The active nature of users in their decision-making and selection of media is consistent with the social media context, where users choose not only to consume but to engage with the media. We seek to understand the impact of this decision-making, and therefore we extend the application of UGT to determine the engagement behaviour (Dolan *et al.*, 2016). Our study contributes to explaining social and affective motivations in the use of social media to express reactions, i.e. what are the *gratifications* of sharing emotions and opinions with others while using Facebook reactions.

It has been observed that people who use social media receive more social and emotional support from others (Hampton *et al.*, 2011). Therefore, this study aims to investigate *how* people use social media interactions to satisfy their social-emotional needs, i.e. *what* emotions people experience and *how* they carry them out throughout online communications channels. The basic ways that users can react or interact with social media content are by *liking*, *sharing*, *commenting*, and/or by choosing some of the *reactions* (or, emojis) as a response to the read content.

Emotional aspects of the content may impact whether it is shared. Rimé *et al.* (1991) created the term "social sharing of emotions" to name the observed phenomenon that most emotional experiences are shared and discussed to make sense of their experiences, reduce dissonance or deepen social connections. Positive or negative emotional experiences can leave lasting social and cognitive traces. After experiencing an emotional event, it is common for people to cognitively replay and reassess the event to make sense of it. Cognitive reassessment of positive emotional experiences reactivates positive emotions, boosting feelings of self-esteem and self-efficacy (Zech *et al.*, 2004). Cognitive reassessment of negative emotions can reduce cognitive dissonance and promote understanding of how the emotion-causing event fits into one's life narrative (Guerra *et al.*, 2014). Social contact and conversations aid in sense-making through the opportunity to retell the story and make social comparisons (Kampić and Bagić Babac, 2021); they can also lead to the provision of support and solidarity. Thereby, we propose the following hypothesis:

H1. User reaction to a posted message on social media is stimulated by emotion.

Using a data set of the *New York Times* articles published over three months, Berger and Milkman (2012) examined how emotion shapes virality (i.e. a number of comments and shares), and their results indicate that positive content is more viral than negative content, but the relationship between emotion and social transmission is more complex than valence alone. Thus, we hypothesize:

H2. Positive content is liked by users more frequently than negative content.

Furthermore, we draw on the emotion theories in an attempt to find emotional patterns on social media and their possible causes and consequences. For instance, Festinger's (1962) theory of cognitive dissonance says that the presence of a cognitive inconsistency of sufficient magnitude will evoke a negative emotional state that will motivate cognitive work aimed at reducing the cognitive inconsistency. Cognitions can be beliefs, attitudes, values and feelings about oneself, others or the environment. Thus, the theory of cognitive dissonance is concerned with the cognitive antecedents of emotion, the intensity of emotional response and the cognitive regulation of this emotional response (Harmon-Jones, 2000).

More specifically, emotional dissonance is "a feeling of unease that occurs when someone evaluates an emotional experience as a threat to his or her identity" (Jansz and Timmers, 2002). Emotional dissonance occurs when expressed emotions satisfy the feeling rule, or role expectations pertaining to an emotional expression that comes with the job rule, but clash with inner feelings. Hochschild (1983) defined emotional dissonance as: "maintaining a difference between feeling and feigning". We seek examples of explicit emotional patterns of cognitive and emotional agreement and/or dissonance, and how they are incorporated through the use of reactions to different types of online news. Based on these possible emotional experiences and their consequences, we set the following hypotheses:

H3. Positive content influences positive user comments.

H4. Negative content influences negative user comments.

Here, we make a clear distinction between the user comments and user reactions. While the user comments are explicit text items that express user opinion usually relating to the published post, user reactions are not expressed via text, but rather as a special encoding (so-called emojis) added to each Facebook post. Therefore, when referring to the content of a post or comment, we do not consider user reactions, but the structure of the content itself.

Furthermore, based on Yahoo Kimo News, Lin *et al.* (2008) created data sets with news articles and the emotions users expressed after reading the articles, from a fixed set of eight emotions. The authors pointed out that the emotions expressed in the news content are not necessarily the same as those expressed by the readers. Rao (2016) and Li *et al.* (2017) also collected data sets with news articles and user ratings across eight emotions, to predict the predominant emotion of each article and the percentage of votes that users will express for the defined set of emotions in each article. In all these three works, readers express their emotions by choosing emoticons from a fixed set established by the websites. Authors argue that emoticons are related to some specific emotions, even though readers do not express their opinions in a written form (Gambino *et al.*, 2018).

Therefore, we hypothesize over a range of different degrees of positive and negative emotions:

H5. Joyful content influences joyful comments.

H6. Surprising content influences surprising user comments.

H7. Anticipatory content influences anticipatory user comments.

Then, from the relationship between the user reactions and the emotional content of posts, we propose the following hypotheses:

H8. Joyful content is correlated to user love reactions.

H9. Surprising content is correlated to laughing user reactions.

H10. Sad content is correlated to sad user reactions.

Moreover, from the relationships between user comments and reactions, we hypothesize:

H11. Joyful user comments are correlated to love user reactions.

H12. Sad user comments are correlated to sad user reactions.

H13. Fearful user comments are correlated to sad and angry user reactions.

In addition, based on the network of posts (Jackson, 2008), we explore if there is a relationship between the structure of the network and the emotional properties of the posts, and thus, we hypothesize:

H14. Centrality measures are correlated to user reactions.

H15. Centrality measures are correlated to the content of the posts.

Here, centrality measures are defined over a network of posts, as explained in more detail in the next section.

3. Research methods

3.1 Data collection and analysis

For the purposes of data analysis, the posts with user opinions from 15 Facebook news portals published between 1 January and 30 June 2018, were retrieved. After filtering the noisy information, i.e. posts without reactions (those with emotion dimensions set to zero), stop-words, non-English words, numbers, URLs and hashtags, we obtained a total of 11,127 posts and 5,505,997 user comments in our data set.

The number of fans on each of the pages in the data set has been recorded on 28 May 2018. The news portals were chosen because of their larger circulation in the USA and their large number of fans (Choi *et al.*, 2020). The number of fans for each portal page with a number of posts and user comments retrieved from that page is given in Table 1.

Each post has its own number of *Likes*, *Shares*, *Comments*, and reactions (*Angry*, *Haha*, *Love*, *Sad* and *Wow*), which are emojis that people can click to express their emotions towards the post. Table 2 shows the summary statistics of emotional (*Angry*, *Haha*, *Love*, *Sad* and *Wow*) and viral (*Likes*, *Shares* and *Comments*) reactions calculated for the total news portal data set. It can be observed that we have taken into calculation the posts with zero votes per reaction. However, those posts with a total of zero votes were discarded, as they did not contribute to our analysis.

Based on this data set, multiple linear regression models are proposed to test the hypotheses, and exploratory factor analysis has introduced additional value to these findings focusing on individual news portals and thus reinforcing some of the regression outcomes.

3.2 Classification of variables for the regression models and exploratory factor analysis

In this paper, the exploratory factor analysis is based upon a space of posts, where each post is assigned a textual message and a set of variables, namely, *behavioural* and *structural*

Table 1 A number of posts and comments appeared on Facebook news pages between 1 January and 30 June 2018, and a number of fans on 28 May 2018

News portal	Fans	Posts	Comments
ABC News	12,987,064	600	387,393
BBC News	46,663,616	854	688,712
CBS News	4,750,373	654	320,932
CNN	30,251,773	795	1,062,187
Fox News	16,414,115	428	935,135
Huffington Post	9,858,289	678	216,253
Los Angeles Times	2,731,700	857	77,845
NBC News	9,715,723	772	355,936
New York Times	15,707,014	1.023	283,640
NPR	6,300,058	750	247,988
The Guardian	7,756,557	741	146,455
USA Today	7,580,084	761	233,928
Wall Street Journal	6,201,146	708	32,416
Washington Post	6,161,639	838	157,813
Yahoo	14,547,436	668	359,364

Table 2 Summary statistics of the news data set by emotional and viral reactions

	Summary statistics					
Dimension	Min.	1st Qu.	Median	Mean	3rd Qu.	Max
Angry	0	1	8	266	77	41.580
Haha	0	3	14	183	77	46.303
Love	0	5	27	438	159	109.328
Sad	0	1	8	221	58	50.178
Wow	0	7	26	183	96	24.599
Like	4	182	530	2.285	1.756	25.483
Share	0	53	177	1.428	662	351.082
Comment	1	37	123	530	418	47.789

variables. These variables allow for measuring different aspects of user behaviour, and therefore, the goal of the factor analysis is to infer how these variables are interconnected based on the observed posts.

Here, we use the term *behavioural* variable for the variable which refers to a certain pattern of user behaviour (in our case, observed from social media), e.g. user reaction to a published post; for instance, how many users have chosen the *Love* reaction to the post, or how many users *liked* the post. Note that a behavioural variable refers to a collective behaviour pattern.

Furthermore, we use the term *structural* variable for a variable that is based either on the internal structure of a post, namely, the *intra-structural* variable; or on the *inter-post* structural overlap, namely the *inter-structural* variable. An *intra-structural* variable refers to the syntax and semantics of a set of words that constitute a post, as well as to the additional properties of these words, e.g. their emotional intensity, valence, etc. In addition, an *inter-structural* variable refers to the relation between the posts, which is based on their respective structures (that is, on a subset of words that the posts have in common).

More specifically, the value of an intra-structural variable is calculated from particular properties of the words that constitute a post. Therefore, such measurement is highly dependent on the research domain. For instance, to measure the sentiment value of the post, it is necessary to have a domain dictionary that provides a sentiment to each word item, as well as an algorithm to calculate the overall sentiment of the post from the sentiment values of individual words. An example of an inter-structural variable is the degree of centrality of the post from a network of posts, in which a post is a node, and the connection between two posts exists if two posts have at least one word in common. Consequentially, the degree of centrality for each post (or node) is the number of posts to which the post is connected.

While posts can obviously be related based on their structure, e.g. two posts are related if they contain the common word(s), less is known if they can be related by behavioural parameters, e.g. if two posts have the same number of *likes*, it is not obvious whether it implies any kind of a relation between them, and if it does, what kind of a relationship would it be, etc.

In this study, the values of the following behavioural variables are retrieved directly from social media: *v.Likes, v.Shares, v.Comments, r.Angry, r.Haha, r.Love, r.Sad* and *r.Wow*. Here, the *v.Likes, v.Shares* and *v.Comments* represent the counts of how many users liked, shared or commented on a particular post, therefore they are prefixed with *v.* as they refer to viral indices of the content. The *r.Angry, r.Haha, r.Love, r.Sad* and *r.Wow* variables represent emotional reactions to a particular post, e.g. how many users expressed a sad (*r.Sad* variable) reaction to a post, etc. They are prefixed with *r.* as they refer to r*eactions*.

The groups of used structural variables are:

- Intra-post: *p.Anticipation, p.Anger, p.Fear, p.Disgust, p.Joy, p.Trust, p.Sadness, p.Surprise, p.Positive, p.Negative;* here, the prefix *p.* stands for the *post*.
- Inter-post: *n.Degree, n.Betweenness, n.Closeness, n.Eigenvalue*; here, the prefix *n.* stands for the *network*.
- Intra-comment: *c.Anticipation, c.Anger, c.Fear, c.Disgust, c.Joy, c.Trust, c.Sadness, c.Surprise, c.Positive, c.Negative*; here, the prefix *c.* stands for the *comment*.

Centrality measures are calculated from the network of the posts. The network is created such that each post is a node, and the connection between two posts exists if two posts have at least one word in common. Otherwise, the posts are not connected.

Betweenness centrality (*n.Betweenness*) measures the extent to which a node lies on paths between other nodes. It is a way of detecting the amount of influence a node has over the flow of information in a graph. Closeness centrality (*n.Closeness*) measures the mean distance from a node to other nodes. It estimates the speed of information through a given node. Degree centrality (*nDegree*) counts how many neighbours a node has. Eigenvector centrality (*n.Eigenvalue*) is a measure of the influence of a node in a network. The gist of eigenvector centrality is to compute the centrality of a node as a function of the centralities of its neighbours (Kramer *et al.*, 2014). For the formulae used to calculate centrality measures, we refer to Jackson (2008).

3.3 Classification of data set items by emotional content attributes

In answer to *RQ1* and *RQ2*, we have explored news content by calculating the emotional values of each post and comment from our data set. The values of intra-post and intra-comment structural variables are calculated using the NRC emotion lexicon and the algorithm (Mohammad and Turney, 2013). The NRC Emotion Lexicon is a list of English words and their associations with eight basic emotions (*anger, fear, anticipation, trust, surprise, sadness, joy* and *disgust)* (Ekman, 1992) and two sentiments (negative and positive). These annotations were manually done by crowdsourcing and applied to a set of 14,182 unigrams (Mohammad and Turney, 2010). Based on the NRC lexicon, we have obtained sentiment scores of posts and user comments, which together with other variables of news posts, provide a framework for the regression models and exploratory factor analysis. We further delve into the causes of emotional responses to online news by exploring how and why people behave when being exposed to specific news content.

4. Experimental results

4.1 Influence of emotions on user reactions and comments

In this section, we provide an answer to *RQ3*. To test *H1* and *H2*, the relationship between the number of comments, shares and likes for each post and its emotional reactions is analysed. Due to the power-law distribution of our data, a Poisson regression model is used to describe a relationship between the variables. The log link function ensures positive fitted values, and the Poisson distribution is typically used for counting data. The set of independent (predictor) variables for the model are *Love, Haha, Wow, Sad* and *Angry*, which represent the amount of *Love, Haha, Wow, Sad* and *Angry* reactions, respectively. The Poisson regression model for testing *H1* and *H2* is as follows:

$$log(Response) = \beta_0 + \beta_1 * Love + \beta_2 * Haha + \beta_3 * Wow + \beta_4 * Sad + \beta_5 * Angry \quad (1)$$

Here, the *Response* is the dependent variable and, depending on the hypothesis, it is a number of comments and shares (*H1*), or likes (*H2*). The list of test outcomes from the regression model for the coefficient estimates (*betas*) is provided in Table 3.

From Table 3, it can be concluded that all emotional reactions influence the number of comments and shares, which confirms *H1* that either positive or negative emotion is a stimulus to participate in a social media activity. However, this evidence is contrary to *H2*, because all emotions, and not only positive as we have hypothesized, influence the *Like*. This indicates that people use the *Like* button for different purposes, even when expressing anger. Here, we assume that *Love* and *Haha* are positive emotions, and *Sad* and *Angry* are negative emotions (Plutchik, 1962), but surprise emotion (*Wow*) may be in some cases positive, and negative in others, so it is highly context-dependent. For the *Sad*, the estimate in Table 3 is negative, which means that if *Sad* increases by one unit, the *Response* reduces $\exp(-1.730 \times 10^{-5})$ times. These results are in accordance with Berger and Milkman's (2012) findings in that the relationship between emotion and social transmission is also in part driven by arousal.

The regression model (1) embodies the UGT (Katz *et al.*, 1973) from the conceptual framework because the explanatory reaction variables contribute to understanding why people actively seek out social media to satisfy emotional needs, i.e. people are gratified with the opportunity to express their emotions, and to get an insight into other people's emotions. The reaction variables propose that the public seeks social communications sources to fulfil an emotional (dis)satisfaction while expanding their social engagements through Facebook. By using Facebook as a means to comment and share the content or choose the emojis, people are also gratified with the reactivation of positive emotions, boosting their feelings of self-esteem (Zech *et al.*, 2004), or handling their cognitive dissonance about the news they have read.

We further propose another regression model for testing *H3–H7*. The set of independent (predictor) variables for the model are *Anticipation, Anger, Fear, Disgust, Joy, Trust, Sadness, Surprise, Positive* and *Negative*, which represent the amount of these emotions in the data item content. The Poisson regression model for testing the hypotheses is as follows:

Table 3 Regression results detailing the influence of reactions on comments, shares and likes

Independent variables	Dependent variable Comments	Shares	Likes
Love	6.056e + 00 ***	4.226e-05 ***	5.673e-05 ***
HaHa	3.765e-05 ***	1.123e-04 ***	8.884e-05 ***
Wow	1.178e-04 ***	1.819e-04 ***	1.184e-04 ***
Sad	2.388e-05 ***	7.886e-05 ***	-1.730e-05 ***
Angry	1.187e-04 ***	8.849e-05 ***	3.698e-05 ***

Note: Significance codes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

$$log(Response) = \beta_0 + \beta_1 * Anticipation + \beta_2 * Anger + \beta_3 * Fear + \beta_4 * Disgust + \beta_5 * Joy + \beta_6 * Trust + \beta_7 * Sadness + \beta_8 * Surprise + \beta_9 * Positive + \beta_{10} * Negative \quad (2)$$

Here, the predictor variables relating to emotional content in comments are *c.* prefixed, and *Response* is *p.* prefixed dependent variable relating to emotional content in posts. Depending on the hypothesis, the *Response* is positive (*H3*), negative (*H4*), joyful (*H5*), surprise (*H6*) or anticipatory (*H7*) emotion. The list of test outcomes for the significant variables is provided in Table 4.

From column (*H3*) of Table 4, it can be concluded that positive emotions from posts *p.Positive* influence positive user comments *c.Positive* ($\beta_9 = 0.122, p < 0.001$). More specifically, positive comments influence comments regarding the *p.Anticipation* ($\beta_1 = -0.069, p < 0.001$), *p.Joy* ($\beta_5 = 0.059, p < 0.01$) and *p.Trust* ($\beta_6 = 0.108, p < 0.001$). For the *p.Anticipation*, the coefficient estimate is negative, which means that if *p.Anticipation* increases by one unit, the *c.Positive* reduces $\exp(-0.069)$ times. If we assume that anticipation, joy and trust are positive emotions, then *H3* is confirmed. Both *H1* and *H3* are positive applications of Katz's (1973) UGT, and also confirm the Zech *et al.* (2004) findings of the cognitive reassessment of positive emotional experiences.

On the other side, column (*H4*) of Table 4 shows that *p.Anger* ($\beta_2 = 0.119, p < 0.001$), *p.Disgust* ($\beta_4 = -0.229, p < 0.001$), *p.Fear* ($\beta_3 = 0.256, p < 0.001$), *p.Sadness* ($\beta_7 = 0.112, p < 0.001$) and *p.Negative* ($\beta_{10} = 0.193, p < 0.001$) are significant predictors for negative comments, which implies that negative content of posts influences negative user comments. However, *p.Positive* ($\beta_9 = -0.172, p < 0.001$) is also a significant predictor for the negative comments, so *H4* is partially supported. In addition to findings of UGT that people use the medium to benefit from gratifications of sharing emotions with others, here we also find evidence that people express negative emotions to release their cognitive dissonance when confronted with bad news (Festinger, 1962).

The (*H5*) column of Table 4 shows an unexpected result that *p.Anger* ($\beta_{10} = -0.188, p < 0.001$), *p.Sadness* ($\beta_7 = 0.119, p < 0.01$) and *p.Negative* ($\beta_{10} = -0.103, p < 0.001$) are significant predictors for the *c.Joy*, in addition to *p.Joy* ($\beta_5 = 0.504, p < 0.001$), which only partially supports the hypothesis. However, this is in accordance with Lin *et al.*'s (2008) finding that the emotions expressed in the news content are not necessarily the same as those expressed by the users.

The (*H6*) column of Table 4 shows that *p.Disgust* ($\beta_4 = -0.257, p < 0.001$), *p.Surprise* ($\beta_8 = 0.723, p < 0.001$) and *p.Negative* ($\beta_{10} = 0.109, p < 0.001$) are significant predictors for the *c.Surprise*, which partially supports *H6*. The (*H7*) column of Table 4 shows that *p.Anticipation* ($\beta_1 = 0.362, p < 0.001$) and *p.Anger* ($\beta_2 = -0.112, p < 0.01$) are significant predictors for the *c.Anticipation*, so *H7* is also partially supported.

To test *H8–H13*, we again use the regression model (1). In the second instance of (1), the predictor variables are emotional reactions to posts' emotional content, and the *Response* is the dependent variable relating to the emotional content of posts or

Table 4 Regression results from testing the relationship between the posts and comments

	Dependent variable				
Independent variables	**c.Positive (*H3*)**	**c.Negative (*H4*)**	**c.Joy (*H5*)**	**c.Surprise (*H6*)**	**c.Anticipation (*H7*)**
p.Anger	−0.071	0.119 ***	−0.188 ***	−0.109	−0.112 **
p.Anticipation	−0.069 ***	−0.012	−0.004	−0.054	0.362 ***
p.Disgust	−0.052	−0.229 ***	0.020	−0.257 ***	−0.055
p.Fear	−0.053	0.256 ***	−0.083	0.048	0.009
p.Joy	0.059 **	−0.108	0.540 ***	−0.034	0.037
p.Sadness	−0.007	0.112 ***	0.119 **	−0.057	0.055
p.Surprise	0.050	−0.062	−0.051	0.723 ***	0.029
p.Trust	0.108 ***	0.048	0.034	0.015	0.030
p.Negative	−0.036	0.193 ***	−0.103 ***	0.109 ***	−0.026
p.Positive	0.122 ***	−0.172 ***	−0.027	−0.067	−0.057

Note: Significance codes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

comments. Depending on the hypothesis, it is *p.Joy* (*H8*), *p.Surprise* (*H9*), *p.Trust* (*H10*), *c.Joy* (*H11*), *c.Sadness* (*H12*) or *c.Fear* (*H13*) emotion. The test results are provided in Table 5.

The (*H8*) column of Table 5 shows that *Love* ($\beta_1 = 2.533 \times 10^{-5}$, $p < 0.001$) and *Wow* ($\beta_3 = -7.652 \times 10^{-5}$, $p < 0.01$) are significant predictors for the *p.Joy*, which partially supports *H8*. It can be noticed that surprise here appears in the context of positive emotions. According to the (*H9*) column, *H9* hypothesis is confirmed, because *HaHa* ($\beta_2 = 4.034 \times 10^{-5}$, $p < 0.001$) is a significant predictor for the *p.Surprise*. Again, the surprise is in the context of positive emotions, but it can be also noticed that *Wow* is not a significant predictor for the *p.Surprise*, indicating that either these variables do not refer to the same emotion, or surprising content does not necessarily imply surprise comments, which is in accordance with Lin *et al.*'s (2008) findings. The (*H10*) column shows that *Sad* ($\beta_4 = 5.575 \times 10^{-5}$, $p < 0.001$) and *Haha* ($\beta_2 = -1.119$, $p < 0.001$) are significant predictors for the *p.Sadness*, which partially supports *H10*.

The (*H11*) column of Table 5 shows that *Love* ($\beta_1 = 4.073 \times 10^{-5}$, $p < 0.001$), *Haha* ($\beta_2 = -4.273 \times 10^{-5}$, $p < 0.001$) and *Angry* ($\beta_5 = -1.995 \times 10^{-4}$, $p < 0.001$) are significant predictors for the *c.Joy*, which partially supports *H11*. According to the (*H12*) column, *H12* hypothesis is also partially supported, because all but *Love* reactions are significant predictors for the *c.Sadness*. The (*H13*) column shows that *Sad* ($\beta_4 = 4.601 \times 10^{-5}$, $p < 0.001$), *Angry* ($\beta_5 = 5.317 \times 10^{-5}$, $p < 0.001$) and *HaHa* ($\beta_2 = -4.743 \times 10^{-4}$, $p < 0.001$) are significant predictors for the *c.Fear*, which partially supports *H13*. Compared to *H8*–*H10*, it can be noted that *H11*–*H13* show a mixture of positive and negative predictors, which is also the evidence in support of Lin *et al.*'s (2008) findings.

Finally, *H14* is tested based on a regression model (1), and *H15* is based on a regression model (2). In both settings, the dependent variable is a centrality measure, respectively. The independent variables are emotional reactions to the posts in testing *H14*, and posts' emotions in testing *H15*. From regression outcomes shown in Table 6, it can be observed that for betweenness and degree centralities, both hypotheses are confirmed, because all predictor variables are significant for the dependent variable. For closeness centrality (omitted from the table), both *H14* and *H15* are rejected as none of the predictors are significant. For eigenvalue centrality, *H15* is partially supported as only *p.Joy* ($\beta_9 = -0.129$, $p < 0.001$), *p.Surprise* ($\beta_8 = 0.225$, $p < 0.001$), *p.Trust* ($\beta_6 = 0.122$, $p < 0.001$) and *p.Positive* ($\beta_{10} = 0.075$, $p < 0.001$) are significant predictors. Overall, it is safe to conclude that both hypotheses are partially supported.

4.2 Influence of emotions on individual news portals

In this section, exploratory factor analysis (EFA) was used to find out the underlying factors in the motivation for participating in online news portals. The answers to the following questions for each of the individual news portals from the data set are given:

- What is the number of underlying patterns (factors), how many factors best fit the data and what are the underlying pieces?
- How do the variables group together?
- Which variables can be eliminated as not being important?

The following EFA analyses were conducted using guidelines outlined in Preacher *et al.* (2003). Bartlett's test indicated correlation adequacy, and the Kaiser–Meyer–Olkin test

Table 5 Regression results from testing the relationship between the posts/comments' emotions and reactions

	Dependent variable					
Independent variables	**p.Joy (*H8*)**	**p.Surprise (*H9*)**	**p.Sadness (*H10*)**	**c.Joy (*H11*)**	**c.Sadness (*H12*)**	**c.Fear (*H13*)**
Love	2.533e-05***	2.773e-06	5.235e-06	4.073e-05***	−4.149e-05	−1.278e-05
HaHa	−1.417e-06	4.034e-05***	−1.119e-04***	−4.273e-05***	−5.032e-04***	−4.743e-04***
Wow	−7.652e-05**	−1.114e-05	9.149e-06	−5.246e-05	−3.544e-04***	−6.379e-06
Sad	−6.757e-06	5.480e-06	5.575e-05***	−2.893e-05	5.854e-05***	4.601e-05***
Angry	−2.256e-05	2.704e-05	−7.572e-06	−1.995e-04***	6.300e-05***	5.317e-05***

Note: Significance codes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 6 Regression results on the relationship between the centrality measures and emotions

Independent variables	Dependent variable Betweenness	Degree	Eigenvalue
(H14)			
Love	6.131e-06 ***	5.429e-06 ***	7.051e-06
HaHa	−1.737e-06 **	3.250e-05 ***	3.344e-05
Wow	−1.009e-04 ***	−1.956e-05 ***	−4.618e-05
Sad	9.083e-06 ***	−1.141e-05 ***	−2.515e-05
Angry	2.025e-05 ***	2.279e-05 ***	2.535e-05
(H15)			
p.Anger	0.019 ***	−0.023 ***	−0.026
p.Anticipation	0.098 ***	0.021 ***	−0.009
p.Disgust	−0.018 ***	0.018 ***	0.043
p.Fear	0.008 ***	0.008 ***	−0.018
p.Joy	−0.167 ***	−0.095 ***	−0.129 ***
p.Sadness	0.024 ***	−0.041 ***	−0.058
p.Surprise	0.151 ***	0.139 ***	0.225 ***
p.Trust	0.132 ***	0.087 ***	0.122 ***
p.Negative	0.088 ***	0.023 ***	0.022
p.Positive	0.127 ***	0.067 ***	0.075 ***

Note: Significance codes: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

indicated sampling adequacy for each EFA instance. Maximum likelihood estimation was used with direct *oblimin* rotation (a non-orthogonal oblique solution) because of the expected factor correlation.

The results of the 15-factor analyses, each corresponding to a single news portal, are summarized in Figure 1. The colours in the figure are used only to distinguish between different factors in a single column, so the same colour in different columns does not imply that the factors have something in common. However, the variables of the same colour in the same column belong to the same factor.

It can be noticed that there exist no pair of columns identical by factor variables, which indicates different user behaviour on these portals. It can be noticed that for the majority of the portals the variables are grouped into five factors, with the exception of Yahoo, which has six factors, and BBC, CNN, Fox and *New York Times*, which have four factors. It is obvious from Figure 1 that none of the viral or reaction variables appeared in a common factor with any of the post/comment emotion variables nor any of the network centrality variables.

4.2.1 Factorization of viral and reaction variables

From Figure 1, it can be noticed that the viral variables are grouped along with reaction variables for all factors, i.e. none of the factors is consisted of only viral variables, which is evidence in support of *H1*, that different emotions stimulate social media activities.

The *Angry* reaction is the least factorized variable in the figure (e.g. it only appears on *Huffington Post*, *WA Post* and *Yahoo* pages as a constituent variable), suggesting that people either avoid writing about what makes them angry, or the content on social media has no intention to evoke such emotional reaction. Based on emotion dissonance (Jansz and Timmers, 2002), people avoid participating in discussions that make them feel bad about themselves, or what is in contrast to their expectations. Expectation dissonance creates these unpleasant emotions (Hochschild, 1983), and people *a priori* avoid reading articles that are not in accordance with their beliefs. On the other hand, an angry emotion does not correlate to our set of other variables, so it might be the case that either online news does not cause such emotion, or it is caused by other online content which is not significantly present in online news.

Figure 1 Factor loadings per factors for the news portals

Variables	ABC	BBC	CBS	CNN	Fox	Guardian	Huffington	LAT	NBC	NPR	NYT	USA	Wallstreet	Washington	Yahoo
v.likes	1.00	0.97	0.88	0.99	0.99	0.88	0.96	0.96	1.00	0.98	0.94	0.96	1.00	0.93	0.69
v.comments	0.42	0.65	0.76	0.40		0.93	0.70	0.50			0.39	0.78	0.72	0.35	0.49
v.shares	0.73	0.81	0.86	0.77	0.88	0.88		0.85		0.57	0.81	0.97	0.79	0.90	0.98
r.angry							0.87							0.65	1.00
r.haha	0.35		0.86						0.43				0.42		
r.love	0.86	0.90	0.95	0.87	0.83	1.00	0.97	0.98	0.96	0.82	0.94	0.99	0.84	0.92	0.49
r.sad			0.36			1.00	0.51					0.90		0.78	0.92
r.wow	0.31	0.59		0.44			0.70				0.36		0.54	0.52	1.00
p.anger	0.77	0.76	0.76	0.83	0.82		0.84	0.77	0.79	0.76	0.63	0.85	0.79	0.80	0.76
p.anticipation	0.63	0.72			0.57	0.73	0.66	0.61	0.50	0.59	0.69	0.67			0.60
p.disgust	0.50	0.52	0.59	0.51	0.51		0.58	0.56	0.51	0.59	0.45	0.58	0.60	0.61	0.59
p.fear	0.78	0.75	0.74	0.86	0.83		0.81	0.72	0.74	0.75	0.61	0.79	0.74	0.80	0.73
p.joy	0.84	0.81			0.69	0.87	0.87	0.83	0.73	0.82	0.82	0.86			0.88
p.sadness	0.63	0.63	0.75	0.66	0.63		0.65	0.70	0.60	0.68	0.54	0.76	0.68	0.64	0.68
p.surprise	0.47	0.47				0.39	0.34	0.36	0.32	0.36	0.41	0.44	0.30	0.38	0.52
p.trust	0.57	0.67	0.35		0.57	0.74	0.58	0.59	0.68	0.60	0.56	0.56	0.36	0.44	0.65
p.positive	0.79	0.73			0.67	0.86	0.73	0.75	0.79	0.70	0.70	0.74		0.35	0.85
p.negative	0.88	0.79	0.92	0.89	0.84	0.38	0.88	0.87	0.88	0.87	0.61	0.92	0.86	0.80	0.86
c.anger	0.47	0.65	0.80		0.44	0.79	0.36	0.73	0.64	0.80	0.74	0.76	0.80	0.34	
c.anticipation	0.65	0.46	0.37	0.70	0.42				0.37				0.78	0.58	0.74
c.disgust	0.39	0.45	0.53			0.58		0.64	0.50	0.43	0.55	0.78	0.74		
c.fear	0.54	0.64	0.79		0.49	0.80		0.67	0.78	0.80	0.76	0.76	0.80	0.31	0.33
c.joy	0.57	0.55		0.67	0.49		0.30		0.36				0.91	0.63	0.68
c.sadness	0.44	0.54	0.66			0.69		0.69	0.67	0.56	0.68	0.70	0.75	0.38	0.36
c.surprise	0.51	0.32	0.39	0.38					0.37			0.39	0.58	0.32	0.64
c.trust	0.73	0.41	0.50	0.62	0.35	0.42			0.51	0.34			0.80	0.68	0.70
c.positive	0.68	0.49	0.48	0.61		0.40			0.40				0.84	0.72	0.46
c.negative	0.32	0.57	0.65		0.38	0.69		0.66	0.48	0.64	0.71	0.76	0.83		0.31
n.betweenness	0.82	0.75	0.86	0.78	0.76	0.83	0.72	0.76	0.77	0.88	0.70	0.82	0.88	0.81	0.50
n.closeness	0.97	0.32	0.95	0.97	0.98	0.25			0.67	0.75	0.63	0.49	0.94	0.63	0.58
n.degree	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
n.eigenvalue	0.98	0.97	0.98	0.98	0.97	1.00	0.93	0.93	0.97	0.98	0.99	0.93	0.99	0.96	1.00

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In the rest of the section, we extract factors from Figure 1, where their ordering is completely at random, and the number dedicated to each factor has no other meaning, but the unique name of a factor. In addition, it is important to extract them to find how much of the factors repeat, only in terms of variable groupings, and not by any factor loading values.

The *r.Angry* variable is factorized as follows:

- Factor r_1: *v.Comments, r.Angry, r.Sad, r.Wow* (Huffington);
- Factor r_2: *v.Comments, v.Shares, r.Angry, r.Sad, r.Wow* (Washington); and
- Factor r_3: *r.Angry, r.Sad* (Yahoo).

From these factors, it is safe to conclude that sad emotion on these pages is closely tied to anger. There is also a certain connection to surprise. On *Huffington* and *Washington Post* pages people feel free to comment about the bad news, while on the Yahoo page people express their negative feelings about the content, but they do not share or comment much. If we choose to interpret factors r_1, r_2 and r_3 in terms of what might have caused such user behaviour, we may recall the theory of cognitive dissonance (Festinger, 1962), that a negative emotional state initiates a reduction of cognitive inconsistency. So, we perceive the behaviour as a direct consequence of the dissonance between the expected and observed, and an action of commenting, sharing or choosing a particular reaction (in this case, from a class of negatives) is the act of actual reduction of such conflict. In addition, both angry and surprise emotions include much of the arousal substance of the emotion Berger and Milkman (2012), which complements the finding of dissonance reduction by exhibiting negative emotions.

According to the factorization of the *r.Haha* reaction, it can be observed that humour is only present in four factors (at ABC, CBS, *NYT* and *Wallstreet* pages), indicating that such reaction is not a very common reaction on news pages. The explanations may be the same as for the angry emotion since both emotions have strong arousal and valence features (Russell, 1980).

From the factors table, it can be seen that the *r.Haha* variable is tied to:

- Factor r_4: *v.Likes, v.Comments, v.Shares, r. Haha, r.Love, r. Wow* (ABC, Wallstreet);
- Factor r_5: *v.Comments, v.Shares, r.Haha, r.Sad (CBS);* and
- Factor r_6: *v.Likes, r.Haha, r.Love* (NBC).

From these factors, it can be seen that *r.Haha* relates to positive emotions at ABC, NBC and *Wallstreet*, so it can be concluded that either these pages offer more positive content, or present the content in such fashion. People also feel free to express their positive emotions on these pages, both by commenting, sharing and liking the content, as well as choosing these particular emotions from the reaction list.

The factors r_4 and r_6 contribute to *H2* that people feel good about the content that is in accordance with their expectations, i.e. without cognitive dissonance, and indicate that people like to replay and take part in the activities that confirm their self-satisfaction (Zech *et al.*, 2004).

It seems unexpected to observe a factor r_5 that includes both *r.Haha* and *r.Sad* variables. However, the interpretation may be related to either different perceptions of the content by different users, or it may be the case that the CBS page publishes ironic, sarcastic or similar ambiguous content that amuses people (Calderon and Kuo, 2019). The possible explanation of such a pattern is also in strong polarity of the content, for instance, when people have opposite attitudes towards certain entities, or events (e.g. sporting events such as soccer competitions, or political elections with opposite candidates or parties). This would further imply that such pages attract readers of different profiles and that a page does not prefer any particular side of the target issues.

The *r.Wow* reaction is factorized (besides for the factors r_1, r_2, r_4) as follows:

- Factor r_7: *v.Likes, v.Comments, v.Shares, r.Love, and r.Wow* (appeared four times).

It can be noticed from here that the *r.Wow* has appeared six times in factors with positive emotions, in contrast to two times in factors with negative emotions.

The *r.Sad* reaction is factorized (besides for the factors r_1, r_2, r_3 and r_5) as follows:

- Factor r_8: *v.Shares, v.Comments, r.Sad* (*Guardian*); and
- Factor r_9: *v.Likes, v.Comments, v.Shares, r.Love, r.Sad* (USA).

Although it may seem unusual to observe both *r.Love* and *r.Sad* in the same factor, it is actually a common reaction when people read about sad content that they show their compassion with a love reaction. Therefore, the difference between the factors r_8 and r_9 might be in the intensity of sad emotions. These findings are in accordance with *H5*.

4.2.2 Factorization of the post and comment variables

While it is expected that the positive content of posts or comments is grouped into the same factor, it is much more interesting to notice if positive posts influence positive comments, or if negative posts influence negative comments (*H3* and *H4*). According to the emotions inferred from the text, the posts are factorized as shown in Table 7:

Here, factor p_1 appeared at seven pages, while p_2 appeared at nine pages. The factors p_1, p_2 and p_4 are expected to appear because they group variables from a similar context, e.g. positive/negative emotions with different intensities are grouped together. These findings are in line with *H3* and *H4* in that people react positively to what makes them feel good about

Table 7 Factorization of the post variables

Factor	In pages	p.Anticipation	p.Anger	p.Disgust	p.Fear	p.Joy	p.Sadness	p.Surprise	p.Trust	p.Positive	p.Negative
p_1	7	✓				✓		✓	✓	✓	
p_2	9		✓	✓	✓		✓				✓
p_3	1	✓	✓			✓		✓	✓	✓	
p_4	1			✓	✓		✓				✓

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themselves and reinforces their positive attitudes towards a particular entity or event, and people react negatively when they experience unpleasant observation that is not in accordance with their beliefs or expectations (Festinger, 1962). Yet, it is interesting to observe the factor p_3, present on one page (ABC), that groups a collection of positive emotions with *p.Anger*, which may indicate the presence of ambiguity or polarity in a post.

The factors that combine posts and comments are shown in Table 8:

Groups of variables in factors pc_3–pc_9 unveil the same pattern of user behaviour about negative content, as stated in *H4*, that people write negative comments related to negative content. This supports the theories of cognitive dissonance (Festinger, 1962) and UGT (Katz *et al.*, 1973) as it reinforces the strength of social media as a means of reducing the dissonance while allowing for writing different opinions. In addition, factors pc_1 and pc_2 are in accordance with *H3*, that people write positively when exposed to positive content. This again allows for the interpretation of UGT that people are gratified with opportunities to share their positive experiences and boost their positive emotions.

It can be also noticed from the factor list that surprise is correlated to positive emotions on BBC page.

The comments are factorized as shown in Table 9:

Here, five factors (c_3–c_7) show a mixture of positive and negative emotions in user comments, which indicates that, on these news portals, people perceive the same content differently and that people feel free to express their different opinions. More in-depth analysis of these comments (based on actual topics) would discover if people disagree among themselves or about the content. In factor c_1, the surprise is grouped with positive emotions, and in factor c_8, it is grouped with negative emotions, which indicates that surprise is a highly context-dependent emotion.

4.2.3 Factorization of the network variables

The network centrality variables are factorized as shown in Table 10:

The grouping of centrality measures is expected due to their methods of calculation and interpretation, i.e. they relate to the structure of the network of posts. The most frequent factor that

Table 8 Factorization of the post and comment variables

	Factors (page)								
Variable	pc_1 (BBC)	pc_2 (Fox)	pc_3 (*NYT*)	pc_4 (BBC)	pc_5 (Fox)	pc_6 (*Huffington*)	pc_7 (*Washington*)	pc_8 (Yahoo)	pc_9 (*Guardian*)
p.Anticipation	✓	✓							
p.Anger			✓	✓	✓	✓	✓	✓	
p.Disgust			✓	✓	✓	✓	✓	✓	
p.Fear			✓	✓	✓	✓	✓	✓	
p.Joy	✓	✓							
p.Sadness			✓	✓	✓	✓	✓	✓	
p.Surprise									
p.Trust	✓	✓							
p.Positive	✓	✓							
p.Negative			✓	✓	✓	✓	✓	✓	✓
c.Anicipation	✓	✓							
c.Anger			✓	✓	✓	✓			✓
c.Disgust			✓	✓					✓
c.Fear			✓	✓	✓		✓	✓	✓
c.Joy	✓	✓							
c.Sadness			✓	✓					✓
c.Surprise									
c.Trust	✓	✓							
c.Positive									
c.Negative			✓		✓			✓	✓

Table 9 Factorization of the comment variables

Factor	Page	*c.Anticipation*	*c.Anger*	*c.Disgust*	*c.Fear*	*c.Joy*	*c.Sadness*	*c.Surprise*	*c.Trust*	*c.Positive*	*c.Negative*
c_1	CNN	✓				✓		✓	✓	✓	
c_2	LAT, *Wallstreet*		✓	✓	✓		✓				✓
c_3	NBC	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
c_4	CBS	✓	✓	✓	✓		✓	✓	✓	✓	✓
c_5	ABC	✓	✓	✓	✓	✓	✓	✓	✓	✓	
c_6	Yahoo	✓					✓	✓	✓	✓	
c_7	*Washington*	✓	✓		✓	✓	✓	✓	✓	✓	
c_8	USA		✓	✓	✓			✓			✓

Table 10 Factorization of the network variables

Factor	Page	n.Betweenness	n.Closeness	n.Degree	n.Eigenvalue	p.Trust	p.Surprise	p.Positive	c.Negative
n_1	CNN, Fox, Guardian, NBC, NPR, NYT, USA, Yahoo	✓	✓	✓	✓				
n_2	*Huffington*, LAT	✓		✓	✓				
n_3	ABC, BBC	✓	✓	✓	✓				✓
n_4	CBS	✓	✓	✓	✓	✓			
n_5	*Wallstreet*	✓	✓	✓	✓	✓	✓		
n_6	*Washington*	✓	✓	✓	✓	✓	✓	✓	

appeared 8 times is n_1, but it did not correlate to any other type of variable except for the network ones.

It is interesting to observe that on the CBS page, the centrality of posts relates to trust, indicating that CBS mostly uses (or, chooses) the set of words labelled with the trust emotion when publishing online (factor n_4). Then, ABC and BBC pages publish in such a way that the centrality of posts is related to negative comments, which indicates that the most frequent words used on these pages attract many negative comments, or that the most central posts tend to be the viral ones. On the other hand, *Wallstreet* and *Washington Post* show that the centrality of posts relates to positive emotions like trust and surprise, which might imply that the most frequently used words on these pages are positive, and present mostly either the positive aspects of news or use the positive approach in presenting any kind of news (factors n_5 and n_6).

Although not present for each news page, certain connections between the network structure of the posts and emotion variables did appear, so they give us an impression of what kind of news, or indirectly, what news writing style appeared online at individual news portals.

5. Discussion

5.1 Conclusions

On social media, the goal of publishing a post is to attract an audience by providing value, or gratification, through its content. Therefore, a post should be designed in a way that creates value for individual users to build a stronger level of engagement and facilitate value outcomes (Malthouse *et al.*, 2013). The essence of achieving this goal is in emotion. Depending on the evoked emotions, the reader of the content decides on how to continue with his/her actions, i.e. to engage more deeply with the medium, or to leave. Therefore, we have analysed the user reactions and comments to find out what kind of emotions appear in response to news on social media, and how they influence user behaviour. The theoretical model and corresponding hypotheses addressed the dynamic nature of how social media content impacts user participation.

Our results have confirmed a subset of the hypotheses, such as that emotion is a stimulus to a particular pattern of behaviour (*H1*), or that positive emotions usually influence positive comments (*H3, H8*), while negative emotions influence negative comments (*H4, H10*). When people read news about successful persons or events, sometimes they identify themselves with success and reinforce a positive self-image (Zech *et al.*, 2004). However, the most interesting findings are those of unexpected behaviour. For instance, testing *H5* has unveiled that joyful comments were not evoked only by joyful, but also sad and angry posts. One of the possible explanations is that people sometimes feel better about themselves when reading bad news because they feel relief that they did not experience the bad story themselves (Rimé *et al.*, 1991). In opposite, it might be the case that people do not enjoy so much listening about positive events going on, because they feel annoyed and inferior in some of the descriptions where they cannot identify themselves. *H2* implies that positive reactions do not necessarily mean that something good has happened. For instance, people are sometimes compassioned when something bad happens, and they express their empathy via positive rather than negative reactions (*H11–H13*). Therefore, our findings reinforce Lin *et al.*'s (2008) conclusions that the emotions expressed in the news content are not necessarily the same as those expressed by the users. It is also interesting to observe that surprise comments were impacted mostly by negative posts (*H6*).

Regarding *H14* and *H15*, some of the centrality measures (e.g. betweenness and degree centrality) have shown a significant correlation with emotions (e.g. trust), even at some individual news portals, which might have useful implications for the designers of online content. The network of posts is based on the textual structure of posts, so choosing a particular set of words in presenting a news event may evoke a predicted set of emotions (e.g. trust, surprise, positive or negative). Overall, certain centrality measures are correlated with emotions (*H14*), which is a strong indication of how vocabulary and structure of sentences might have far-reaching consequences (*H15*) such as an increase in news consumption or modification of user views or sentiments about particular event or entity. Our findings are promising for future studies, which can lead to the development of new hypotheses and theoretical models about online social interactions in social media.

5.2 Theoretical implications

As social media grow, and users increasingly express their opinions and comments on various topics, automatic emotion detection from the text has attracted growing attention due to its potentially useful applications (Woodruff *et al.*, 2020; Sandoval-Almazan and Valle-Cruz, 2020; Puh and Bagić Babac, 2022).

By providing fine-grained assessments of users' activities, the theoretical contributions of this study are twofold. On one hand, an insight into the emotional reactions of users based on the emotion theories is shown, which provides the marketers and decision-makers with an emotional framework to shape online content according to users' needs (Luarn *et al.*, 2015). Our theoretical contributions may be extended to other domains of interest, beyond the scope of the news domain, e.g. politics, sports, technology. On the other hand, from the presented factor analysis, it is possible to detect details that make one news portal different from the other. By exploring the user reactions in the direction of readership profiling, we may expand our understanding of how and under what circumstances the design of online news spaces helps (or does not help) to cultivate participatory practices among users (Almgren and Olsson, 2016). In addition, the data set as well as the findings from this study may serve data scientists in developing predictive models of user behaviour (Preston *et al.*, 2021).

5.3 Practical implications

Our findings have several practical implications for social media strategies that can help marketers to understand user participation (Dwivedi *et al.*, 2019). Based on the revealed relationship between the various emotional contents and user reactions to it, marketers can structure communication content in such a way that it promotes positive engagement behaviours (Gummerus *et al.*, 2012). Moreover, brand managers that use social media platforms can be guided by this research in deciding which characteristics of content to place within posts to elicit favourable behavioural responses among users (Han, 2021; Molina *et al.*, 2020; Moussa, 2019; Shen *et al.*, 2017).

Reliable emotion detection can help develop powerful human-computer interaction devices. Based on the results presented in this study, emotion detectors can be developed, implemented and tested for various purposes and domains of use. Moreover, the use of machine learning (Cvitanović and Bagić Babac, 2022) and deep emotional analysis of data (Kawade and Waghmare, 2017) could reveal further interesting insights into human nature and behaviour.

5.4 Limitations and future research

While this study has provided interesting insights into user behaviour in an online news setting, it has limitations that need to be addressed. Our observations are based on different news portals in terms of journal policy as well as the targeted audience. For instance, according to Glader (2017), the *New York Times*'s editorial page and some of its news coverage take "a left-leaning, progressive view of the world". Then, *Wallstreet*'s "editorial page is a bastion of American free-market conservatism". *Washington Post* "is arguably the most forward-thinking right now in trying new digital strategies that have boosted readership". The BBC is the global standard-bearer for excellence in broadcast radio and TV journalism. In addition, some of the chosen news portals are among the most popular news brands in the USA (Verto Analytics, 2018), e.g. Fox News, *NY Times*, CNN, *WA Post*, USA Today, *The Huffington Post* and CBS News. Our selection of journals is limited in many aspects, so future avenues of this research might consider a wider range of editorial policies and journals, cultural or language areas, or websites beyond social networks.

Future research could theorise and examine the influence of social media content on a wider range of cognitive and affective dimensions. Also, more in-depth text mining would show the relationship between the topics of posts and user reactions, or topics from the comments. This would provide an even more comprehensive understanding of the engagement attributed to social media content, and consequently, could be a better predictor of future behaviour. Moreover, it would be interesting to compare user reactions or pulse among different cultures, regions or countries.

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