Emotional showdown on social media: analyzing user reactions to the 2016 US presidential campaign

Marina Bagić Babac
Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia

Received 16 February 2023
Revised 27 July 2023
Accepted 13 September 2023

Abstract

Purpose – Social media platforms are highly visible platforms, so politicians try to maximize their benefits from their use, especially during election campaigns. On the other side, people express their views and sentiments toward politicians and political issues on social media, thus enabling them to observe their online political behavior. Therefore, this study aims to investigate user reactions on social media during the 2016 US presidential campaign to decide which candidate invoked stronger emotions on social media.

Design/methodology/approach – For testing the proposed hypotheses regarding emotional reactions to social media content during the 2016 presidential campaign, regression analysis was used to analyze a data set that consists of Trump's 996 posts and Clinton's 1,253 posts on Facebook. The proposed regression models are based on viral (likes, shares, comments) and emotional Facebook reactions (Angry, Haha, Sad, Surprise, Wow) as well as Russell's valence, arousal, dominance (VAD) circumplex model for valence, arousal and dominance.

Findings – The results of regression analysis indicate how Facebook users felt about both presidential candidates. For Clinton's page, both positive and negative content are equally liked, while Trump's followers prefer funny and positive emotions. For both candidates, positive and negative content influences the number of comments. Trump's followers mostly share positive content and the content that makes them angry, while Clinton's followers share any content that does not make them angry. Based on VAD analysis, less dominant content, with high arousal and more positive emotions, is more liked on Trump's page, where valence is a significant predictor for commenting and sharing. More positive content is more liked on Clinton's page, where both positive and negative emotions with low arousal are correlated to commenting and sharing of posts.

Originality/value – Building on an empirical data set from Facebook, this study shows how differently the presidential candidates communicated on social media during the 2016 election campaign. According to the findings, Trump used a hard campaign strategy, while Clinton used a soft strategy.

Keywords Regression analysis, User reactions, Social media, US presidential campaign, Trump, Clinton, Elections

Paper type Research paper

Introduction

The US political campaign system involves candidates competing in primaries for party nominations, followed by a general election where the winner is determined by the Electoral College. In recent years, social media activities have become a prominent aspect of

Global Knowledge, Memory and Communication
Vol. 74 No. 11, 2025
pp. 19-41
Emerald Publishing Limited
2514-9342
DOI 10.1108/GKMC-02-2023-0060

campaigns, with candidates using platforms like Twitter, Facebook and Instagram to connect with voters, share campaign messages and engage in direct interactions with the public (Aragón, 2016). The emergence of social media has brought about a revolutionary shift, creating a new paradigm for political communication and fundamentally altering the foundation of the political process (Gainous and Wagner, 2013), fostering direct dialogues with citizens and facilitating vibrant political discussions (Hong and Nadler, 2011).

The use of Facebook during the 2008 US presidential election demonstrated how powerful social media as a political communication tool can be, with a potential for dialogue that can persuade and incite action (Woolley *et al.*, 2010). Although social media campaigning did not start with Barack Obama, the 2008 US presidential election marked a significant shift in political campaigning, with the Obama campaign making unprecedented use of social media (Cogburn and Espinoza-Vasquez, 2011; Lilleker and Jackson, 2011). Three years later, President Obama broke with convention once again when he publicly announced his reelection bid with a YouTube video and a tweet on April 4, 2011 (Gerodimos and Justinussen, 2015). Four years later, Hilary Clinton followed his example by announcing her presidential campaign with a YouTube video on April 12, 2015. The 2016 election winner, President Donald Trump, did not announce his campaign on YouTube, but according to certain analyses (Bickart *et al.*, 2017), his social media team consistently outperformed Clinton's team throughout the entire presidential campaign, leading up to the election.

In the 2016 election, the supporters of Donald Trump and Hillary Clinton came from diverse social and cultural backgrounds (Campani *et al.*, 2022). However, it is these groups were not uniform, and individual motivations for supporting each candidate varied widely within their respective bases. The election's outcome was shaped by a complex interplay of factors, including policy positions, personal values and the broader political climate during that time (Lacatus and Meibauer, 2021).

Regarding online followers, the findings by Sahly *et al.* (2019) indicated that both Trump and Clinton followers on Twitter were consistently drawn to retweeting posts framed around conflict and morality while favoriting behaviors were more likely to be triggered by emotional frames. However, when it came to Facebook engagement, there was no consistent pattern observed among the followers of the two candidates. Enli's (2017) analysis of the 2016 US presidential elections revealed that the Clinton campaign's strategy confirmed theories regarding the professionalization of election campaigns, while the Trump campaign had a more amateurish yet authentic style in social media, pointing toward de-professionalization and even amateurism as a countertrend in political communication.

Many studies explored the 2016 US election from various aspects, ranging from the roles of hypermasculinity and androgyny in winning the election (Powell *et al.*, 2018) over the influence of political candidate brands (Van Steenburg and Guzmán, 2019) to fake news on social media as one of the most widely debated aspects (Lee, 2019). However, less is known about the relationship between candidate posts and followers' emotions in response to those posts on social media (Sandoval-Almazan and Valle-Cruz, 2020).

This study examines emotional reactions to political Facebook messages during the 2016 US presidential campaign to explore the concept of user engagement in the context of election activities, and to develop and empirically test a research model that explains why candidates conduct certain types of election campaigns, and how they affect users. More specifically, the relationship between viral (*likes, shares, comments*) and emotional Facebook reactions (*Angry, Haha, Sad, Surprise, Wow*) are explored using the regression models. In addition, we draw on Russell's VAD circumplex model of affect (Russell, 1980), which maps emotions on a three-dimensional space (Bradley and Lang, 1994), namely, *Valence* (the degree of positive/negative affectivity), *Arousal* (ranging from calming to exciting) and *Dominance* (going from "controlled" to "in control") to underscore the importance of emotional processes in shaping collective outcomes, which are accordingly highly context-dependent.

The regression results provide insights into how different emotional dimensions (emojis/VAD) influence user engagement (likes, comments, shares) on Trump's and Clinton's social media pages. The findings generally support some aspects of Berger and Milkman's (2012) research on virality and emotional content but also reveal differences in user behavior between the two political pages. These variations underscore the importance of considering context and audience when crafting social media content to optimize engagement.

Theoretical framework

Use of social media during the election campaigns

Social media give politicians a chance to engage constituents in a way that is two-way and symmetrical (Oliveira *et al.*, 2017), as well as provide an opportunity to help politicians better represent opinions of the people they represent (Larsson, 2017). For instance, user engagement can be measured as "observable activities directly connected to specific candidate communications," including comments, likes and shares (Xenos *et al.*, 2017), and other user reactions such as emojis (Kralj Novak *et al.*, 2015; Tian *et al.*, 2017). Such direct communication has "great potential to influence political decision-making, as political actors can derive an opinion climate from user engagement and are confronted with direct feedback of potential voters and opinion leaders" (Bene, 2017).

Moreover, on social media websites, such as Twitter and Facebook, campaigns and other political elites react in near-real-time (Edgerly *et al.*, 2016). However, Samuel-Azran *et al.* (2015) suggest that online engagement was potentially influenced by the political system, candidates' digital communication skills and young age. According to Steenkamp and Hyde-Clarke (2014), the public is using Facebook site(s) to engage in discussions of a political nature as well as using the platform to connect with each other and share political information in new ways. Most studies on public response to election campaigns rely heavily on lists of media motivations and use that were developed in the prenew media era, indicating that voters use internet campaign media for guidance, surveillance/information-seeking, entertainment and social utility (Johnson and Kaye, 2003), as well as to reinforce their voting decisions (Mutz and Martin, 2001) that seems to be a key point that influences reaction (Bagić Babac and Podobnik, 2018).

Bronstein's (2013) content analysis revealed that the Facebook pages were used for fund-raising purposes, and for the mobilization of supporters during the 2012 US elections. In addition, the Facebook pages of both presidential candidates presented an alternative way to do politics called *fandom politics* that is based not on logic or reason, but on the affective sensibility of the audiences, discouraging dissent and encouraging affective allegiances between the candidate and his supporters.

The role of sentiment in political communication

It is well-known that political discourse cannot be reduced to mere information – the tone of a text may be as influential as its substantive content (Young and Soroka, 2012). Numerous studies have focused on the tone or sentiment of news content, political speeches and advertisements (Dang-Xuan *et al.*, 2013; Grčić *et al.*, 2017; Lin and Utz, 2015). Moreover, a substantial and growing body of research suggests that affect is a central component of individual decision-making and political judgment generally, as well as the processing of media information (Young and Soroka, 2012).

The affective aspect of online communication during the election was also observed and studied on Twitter, e.g. Mohammad *et al.* (2014) showed that tweets conveyed negative emotions twice as often as positive ones, based on the 2012 US presidential election tweets. The results of Tumasjan *et al.* (2011) showed that Twitter is used extensively for political deliberation and that tweets' sentiment (e.g. positive and negative emotions associated with a politician) corresponds closely to voters' political preferences.

A study on the role of sentiment in political communication on Twitter (Dang-Xuan *et al.*, 2013) shows that both emotionality and appraisals of political parties or politicians in Twitter messages are correlated with increased viral effects, while another study (Borah, 2016), which deals with the 2008 and 2012 US presidential candidates, shows that certain candidates used Facebook to express fear or anger, while those who used humor and enthusiasm got more support.

In terms of tonality, Heiss *et al.* (2018) found that the effect of negative tone increased comments and shares, whereas the expression of negative emotions increased only likes, and that mere positive tonality did not increase user engagement, but the expression of emotions did. In addition, some previous works have addressed the relationship between emotions and information diffusion, but in other contexts than social media (Luminet *et al.*, 2000; Peters *et al.*, 2009).

An analysis of sentiments on Facebook during the 2016 US presidential election (Alashri *et al.*, 2016), which examined posts and comments by five presidential candidates (Hillary Clinton, Donald Trump, Bernie Sanders, Ted Cruz and John Kasich) from their official Facebook pages, suggests that commentators on Republican candidate pages express negative sentiments toward current public policies as they seldom support decisions made by the Obama administration, while commentators on Democratic candidate pages are more likely to express support for continuation or advancement of existing policies. However, the significance (strong/weak) and nature (positive/negative) of sentiments varied between candidates within political parties based on the perceived credibility of the candidates' degree of credibility on a given issue. Additionally, an analysis showed that changes in online trends are driven by popular posts, offline debates and candidates dropping out of the race (Schill and Hendricks, 2018).

Expressing emotions and receiving feedback may serve the emotional regulation needs of Facebook users (Bazarova *et al.*, 2015). Cognitive reassessment of positive emotional episodes reactivates positive emotions, boosting feelings of self-esteem and self-efficacy (Zech *et al.*, 2004). In other words, people often seek social communications sources to fulfill an emotional satisfaction and to have others agree with the knowledge they think they already have (Puh and Bagić Babac, 2023).

Research focus

Observing the emotions shown on Trump's and Clinton's Facebook pages, this study explores which candidate had a more positive/negative campaign. In other words, this study aims to investigate *how the presidential campaign affects posting activities at candidates' official Facebook pages and how people react to them.* More specifically, it seeks the answers to the following questions relating to reactions to posts at Trump's and Clinton's Facebook pages:

RQ1. What kind of emotions were evoked by the posts published during the presidential campaign in 2016?

RQ2. How do the emotions evoked by the candidates' posts affect post virality?

RQ3. How do the valence, arousal and dominance evoked by the candidates' posts affect their virality?

Based on these research questions, and the theoretical framework, we set the following hypotheses.

H1a. The emotions evoked by political content influence favoritism on social media.

H1b. The emotions evoked by political content influence conversation on social media.

H1c. The emotions evoked by political content influence amplification on social media.

H2a. The valence, arousal and dominance evoked by political content influence favoritism on social media.

H2b. The valence, arousal and dominance evoked by political content influence conversation on social media.

H2c. The valence, arousal and dominance evoked by political content influence amplification on social media.

In this study, *amplification* refers to the act of sharing content on Facebook, and *conversation* refers to the act of commenting on Facebook, while *favoritism* denotes liking activity. Other Facebook reactions are *Love*, *Haha*, *Wow*, *Sad* and *Angry* emojis that people click as a response to the posted content, which are used for the purpose of this study.

The Facebook emojis (*Angry*, *Haha*, *Love*, *Sad* and *Wow*) represent cross-cultural, universal human emotions recognized by universal facial expressions (Ekman, 1992). Each of these emotions can be rated according to its hardness/softness (Sanford, 2007), where hard emotion is associated with power assertion, the pursuit of self-centered goals and negative communication, and soft emotion is associated with expressions of vulnerability, pursuit of pro-social goals and positive communication. For instance, if a person perceives the other as angry, they will recognize a threat, so they will respond with a hard emotion like anger or blame (Bagić Babac, 2023). Or, if a person is perceived to be sad or vulnerable, they will recognize negligence and will respond softly. Likewise, anger, frustration and disappointment are hard emotions, and behind these are often soft emotions like grief, sadness, loneliness and fear (Christensen, 2000). Hard emotions are selfish and associated with exerting power and control, while soft emotions are pro-social. Therefore, if one only expresses hard feelings, this might lead to the escalation of conflicts. To speak about and convey soft emotions might instead create greater intimacy and warmth and reduce conflicts (Reevy *et al.*, 2010). Following these foundations, we have put *Love* and *Sad* into the class of soft emotions, and *Angry*, *Haha* and *Wow* into the class of hard emotions.

It should be noted that emojis have inherent limitations in capturing the complexity of human emotions (Tian *et al.*, 2017). These limitations may lead to challenges in accurately identifying the true sentiment behind users' reactions to candidates' campaigns. In other words, there might be underlying positive or negative sentiments toward both candidates or their posts that emojis might not fully capture, potentially resulting in an incomplete understanding of users' true feelings and responses. As a result, while emojis provide valuable insights into users' immediate reactions, they should be used with caution in making comprehensive assessments of candidates' overall public perception and sentiment.

It should also be noted that the following analyses are based on the observed users' engagement on Facebook, without considering if the content of the posts are appropriate or correct.

In addition, we also explore connections between emotional content and virality, building on Berger and Milkman's (2012) findings that "more positive content is more viral than negative content, and that the relationship between emotion and social transmission is also driven in part by arousal," i.e. content that evokes either positive or negative emotions characterized by high arousal is more viral, while content that evokes low arousal emotion is less viral. Their results hold controlling for how surprising, interesting or practically useful content is (all of which are positively linked to virality), as well as external drivers of attention (e.g. how prominently content was featured), and further demonstrate the causal impact of arousal on transmission and generalize the findings to positive emotions. It has been observed that "arousing delight requires surprise and a positive emotion" (Plutchik, 1980).

Methodology

Data set processing

In April 2017 (when our data set was retrieved), Trump had about 22 million fans, and Clinton had about 10 million fans on Facebook. Using Facebook's Graph API Explorer, we retrieved posts from Trump's Facebook website (www.facebook.com/DonaldTrump/?fref=ts) published from June 16, 2015, when he formally launched his presidential campaign at Trump Tower in New York City, until the Election Day held on November 8, 2016.

For Hilary Clinton, we retrieved posts from her Facebook website (www.facebook.com/hillaryclinton/?fref=ts&rf=106032959437277) published from April 12, 2015, when her presidential campaign was announced in a YouTube video, until the Election Day. Overall, we collected a data set of Trump's 996 posts and Clinton's 1,253 posts.

Our data set contains posts (*message*) with the assigned values of *likes_count*, *comments_count*, *shares_count*, *love_count*, *haha_count*, *wow_count*, *sad_count* and *angry_count* variables for each post. Based on this data set, multiple linear regression models are proposed to test the *H1*(*a–c*) and *H2*(*a–c*), while the first research question (*RQ1*) is answered by analyzing polarity of published posts based on cumulative normalized frequency distributions for each of five emotional dimensions (emojis).

Valence, arousal and dominance analysis

To explore the influence of VAD of emotions, we map the emotions a post is found to evoke to Russell's (1980) VAD circumplex model. Warriner *et al.* (2013) provided norms of valence, arousal and dominance for 13,915 English lemmas, including words representing the emotional dimensions of emojis. Valence denotes the degree of positive/negative affectivity (e.g. *fear* has a high negative valence, while *joy* has high positive valence); Arousal ranges from calming to exciting (e.g. *anger* is denoted by high arousal while *sadness* by low arousal); and Dominance goes from "controlled" to "in control," e.g. *joy*, highly in control vs *fear*, overwhelming (Guerini and Staiano, 2015). Table 1 shows these scores on a Likert scale (Warriner *et al.*, 2013), ranging from 1 (*low/negative*) to 9 (*high/positive*), which we refer to as matrix M_{EC}, where index E stands for emotional dimensions, and index C stands for circumplex dimensions.

After removing stopwords, hashtags, URLs and numbers from our Trump/Clinton data set, two textual corpora (Trump/Clinton) were created. For each corpus, we built a post-by-

Emotion	Valence	Arousal	Dominance
Angry	2.53	6.02	4.11
Haha	8.37	6.32	7.04
Love	8.0	5.36	5.92
Sad	2.10	3.49	3.84
Wow	7.44	6.57	5.17

Source: Table by the author

Table 1.
Valence, arousal and dominance scores for emotion labels

emotion matrix (M_{PE}), providing the voting percentages for each post in the five emotional dimensions available on Facebook (Bagić Babac and Podobnik, 2023). To compute VAD scores for a given post, we multiply the percentage of votes each emotion is found to evoke in a post by the corresponding VAD score provided by matrix M_{EC} and then take the sum over the *n* emotional dimensions considered. To compute these scores for all posts, we applied matrix multiplication between the post-by-emotion (M_{PE}) and emotion-by-VAD matrices (M_{EC}) (Staiano and Guerini, 2014). Under the resulting matrix (M_{PC}), the regression analysis is performed.

It should be noted that the VAD analysis used in this study relies on mapping Facebook emojis to specific words, which could lead to varied interpretations of these emojis based on the semantics of the chosen words. As a result, the emotions conveyed by the emojis may not always align precisely with users' intended sentiments, potentially introducing some degree of ambiguity and subjectivity in the analysis.

Empirical results of emotion analysis

The summary statistics of the posts from Trump's and Clinton's pages are shown in Tables 2 and 3. The differences in these numbers are the consequence of different fan numbers who liked their pages. According to the mean values, it can be noticed that *liking* is the most dominant activity for both pages, followed by *sharing* and then *commenting* for Clinton's page and *commenting* and then *sharing* for Trump's page. The most popular emoji for both candidates is the *Love* emoji, followed by the *Angry* and *Haha* emoji. The only difference in the

			Trump's page			
Variable	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Like	432	41,860	64,290	77,960	96,670	704,100
Comment	49	3,769	6,006	17,350	9,927	1,249,000
Share	0	3,521	7,640	15,470	15,980	657,100
Love	0	4	97.5	4,220	3,826	104,700
Haha	0	1	19	570.5	271	49,650
Wow	0	0	8	209.4	216.2	5,910
Sad	0	1	3	92.49	40	12,840
Angry	0	1	42.5	739.9	418	66,800

Source: Table by the author

Table 2. Summary statistics of posts at Trump's page

			Clinton's page			
Variable	Min.	1st Quartile	Median	Mean	3rd Quartile	Max.
Like	7	6,945	13,220	20,820	23,100	325,800
Comment	2	683	1,400	3,744	3,228	208,300
Share	0	789	1,822	5,902	4,411	492,900
Love	0	1	56	1,729	1,369	57,070
Haha	0	0	4	221.6	111	11,690
Wow	0	0	4	103.2	70	4,754
Sad	0	0	1	139.4	19	50,500
Angry	0	0	10	415.1	153	39,760

Source: Table by the author

Table 3. Summary statistics of posts at Clinton's page

relative emoji distributions by mean values is that Clinton's page has at least *Wow* emojis, while Trump's page has at least *Sad* emojis.

The most emotional moments of the 2016 election campaign

Relating to the first *RQ1*, it is interesting to observe which posts collected the most emojis during the election campaign.

The most *loved* and *wow*, but also the *angriest* post on Trump's page is the one that shows a video of the third debate held on October 19, 2016. The huge number of Facebook reactions can be explained by the peak of emotional excitement of users, as that was the last debate before the election. The message of this post is: "Debate is over but the fight isn't." This one is also the most commented of Trump's posts.

The funniest post on Trump's page is a video clip from the second Presidential debate when Donald Trump retorted: "Because you'd be in jail!" in response to Clinton saying: "Awfully good that someone with the temperament of Donald Trump is not in charge of the laws in this country." This one is also the most shared of Trump's posts.

The saddest post on Trump's page is: "Muhammad Ali is dead at 74! A truly great champion and a wonderful guy. He will be missed by all!" Trump's supporters were sad to read about Muhammad Ali's death, the legendary boxer who proclaimed himself "The Greatest" and was among the most famous and beloved athletes on the planet (Almasy, 2016).

In addition to emojis, the most-liked post on Trump's page dates long before the election campaign and was published on the 2015 Christmas Eve: "Merry Christmas to all. Have a great day and have a really amazing year. Together, we will MAKE AMERICA GREAT AGAIN! It will be done!"

On Clinton's page, the most *loved* post is a video about Clinton's life accompanied by a textual message "This one's for you, Hillary." The video focuses on a warm and touching story about love, work and struggle, and the user response confirms the video's success in terms of emojis.

The most *wow* post on Clinton's page is: "It's time for Trump to answer serious questions about his ties to Russia." The figure itself contains a message.

The saddest and angriest post on Clinton's page is: "When Trump trivializes the sacrifice of our military and veterans, he makes it clear: He has no idea what service to this country means." This one is also the most shared of Clinton's posts.

The funniest post on Clinton's page is a video with a message: "Will Ferrell: comedian, actor, just your average millennial," calling users to vote for Clinton.

Polarity of emotions

The *RQ1* is furthermore answered by an overall emotional picture of both pages, as shown in Figures 1 and 2, with cumulative normalized frequency distributions for each of the five emotional dimensions (emojis).

While it may seem from the figures that the two pages are similar, a statistical test for testing groups for equal proportions is used to compare the number of posts in each emoji category for both pages. The list of test outcomes, i.e. the 95% confidence interval estimate of the difference between the pages' proportions of values, is provided along with χ^2 and *p*-value in Table 4.

The tests show that for all five emotional dimensions, the two pages are significantly different. Trump's page showed significantly more *Love* and *Haha* emotions than Clinton's page, while Clinton's page showed significantly more *Angry, Sad* and *Wow* emotions, which

Figure 1. Emotional proportions overview of the Trump's page

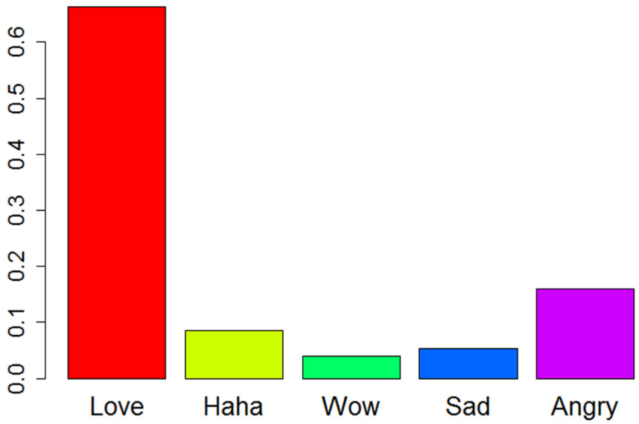

Figure 2. Emotional proportions overview of the Clinton's page

Table 4. Test proportion results for emotions (Trump's vs Clinton's page)

Attribute value	Proportion difference interval	χ^2	p
Love	(0.06001, 0.06126)	36,735	<2.2e-16***
Haha	(0.01249, 0.01327)	4,104	<2.2e-16***
Wow	(−0.00392, −0.00340)	781.86	<2.2e-16***
Sad	(−0.03786, −0.03733)	103,590	<2.2e-16***
Angry	(−0.03274, −0.03178)	18,243	<2.2e-16***

Note: *** Significance level $p < 0.01$

is the evidence that the two candidates used much different election campaign strategies on social media.

Figures 3 and 4 provide a more detailed insight into the polarity of both pages during the period of three months before the election. The x-axes are temporal and discrete, indicating

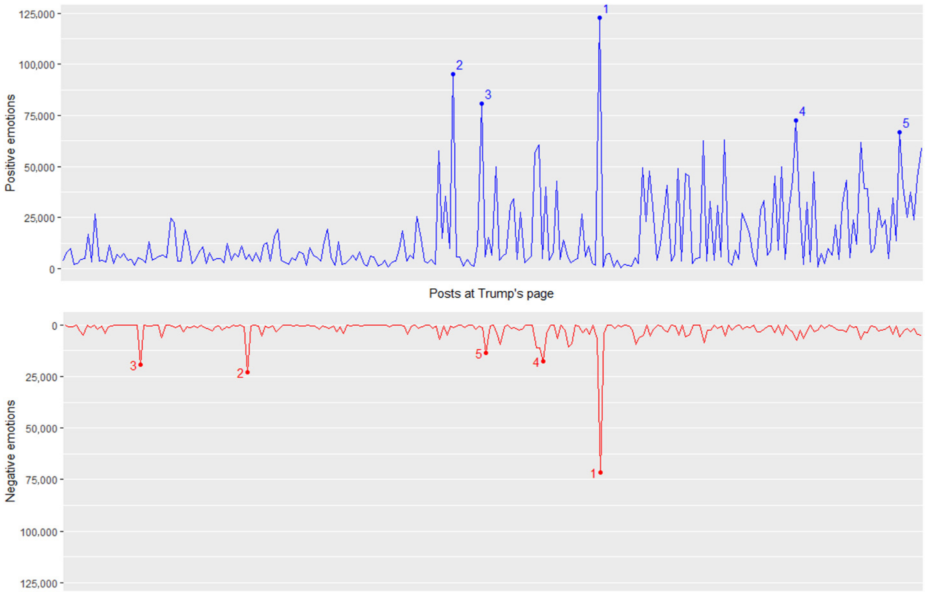

Figure 3.
Positive vs. negative emotions at Trump's page.

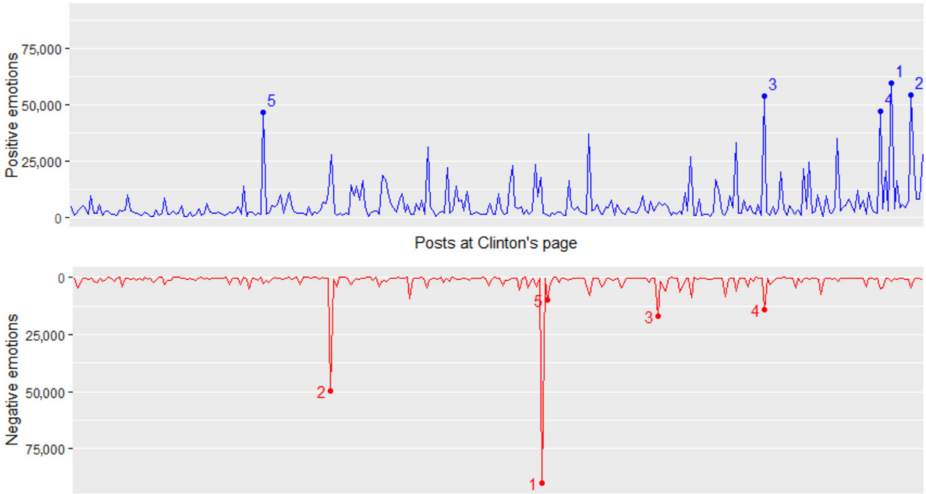

Figure 4.
Positive vs. negative emotions at Clinton's page

when a particular post was published; however, the exact time is removed from the figures due to too much data. The y-axes are discrete sums of positive (*Love*, *Haha* and *Wow* emojis) or negative emotions (*Sad* and *Angry* emojis), i.e. the votes received per post. The top five of the most positive and negative posts are marked as dots in the figures, and therefore, we extract the messages provided along with these posts. It is expected that the most emotional moments from the above reappear in the listing below as they contributed to both the most positive and negative emotions.

The top five of the most positive posts on Trump's page are as follows:

(1) "Debate is over but the fight isn't."

(2) "Because #CrookedHillary would be in JAIL!" (video post).

(3) "Clinton: 'It's a good thing Trump isn't in charge of the law in this country.'

Trump: 'Yeah, because you'd be in jail.'" (photograph post)

(4) "Join me LIVE in Albuquerque, NM!"

(5) "Join me LIVE in Sterling Heights, MI!"

The top five of the most negative posts on Trump's page are as follows:

(1) "Debate is over but the fight isn't."

(2) "Four brave Americans lost their lives in Benghazi and Hillary Clinton falsely said tonight that we did not lose one American life in Libya. SAD!"

(3) "BREAKING: Three FBI field offices wanted to open an investigation into the Clinton Foundation, but it was killed by Obama's Department of Justice."

(4) "This speaks volumes about the RIGGED mainstream media:" along with the photograph: www.facebook.com/DonaldTrump/photos/a.488852220724.393301.153080620724/10157889858965725/?type=3&theater

(5) "All of the moderator interruptions - it was 3 vs 1!" along with the video: www.donaldjtrump.com/content-center/entry/heres-video-of-every-time-the-moderators-interrupted-donald-trump/

The top five of the most positive posts on Clinton's page are the following:

(1) "This one's for you, Hillary."

(2) "Today, I'm asking for your vote. Tomorrow, let's make history together."

(3) "Join Hillary on the trail in North Carolina with Bernie Sanders and Pharrell Williams."

(4) "Hillary and LeBron James are live in Cleveland with two days to go. Watch right here on Facebook."

(5) "Michelle Obama is on the trail for Hillary today in Virginia. Catch it live here."

The top five of the most negative posts on Clinton's page are the following:

(1) "When Trump trivializes the sacrifice of our military and veterans, he makes it clear: He has no idea what service to this country means."

(2) "Trump on Alicia in 1996: 'Miss Piggy.'

This morning: 'She gained a massive amount of weight [. . .] it was a real problem.'"

(3) "FBI Director Comey — who released a vague and misleading letter about Hillary's emails just days before the election — opposed releasing details about Russian interference because he thought it was too close to the election. Incredible."

(4) "Join Hillary on the trail in North Carolina with Bernie Sanders and Pharrell Williams."

(5) "My name is Mae Wiggins. I was denied an apartment in the Trump buildings based on the color of my skin."

When comparing Figures 3 and 4, it may seem that positive vs negative emotions on both pages are similar; however, the correlation coefficient between the positive and negative emotions on

Clinton's page is 0.17325, while it is 0.48388 on Trump's page, indicating a low correlation between Clinton's positive and negative emotions, and high correlation between Trump's positive and negative emotions. This indicates that on Clinton's page public opinion is more unified than on Trump's page, where emotions are more turbulent, i.e. both positive and negative emotions arise at the same time. For instance, on Trump's page, the same post is both maximum positive and maximum negative. The possible explanation for this difference is that Trump is followed by both his supporters and opponents much more than Clinton. Overall, it may seem that Trump attracted much more attention on Facebook than Clinton, which indicates that the two candidates used much different election campaign strategies on social media.

The influence of emotions on virality

In this section, we provide an insight into the relations and influence between virality indices, i.e. the number of *comments*, *shares* and *likes* for each post, and the emotions expressed by emojis. The set of independent (predictor) variables for the regression model are *LoveEmoji, HahaEmoji, WowEmoji, SadEmoji* and *AngryEmoji*, which represent the amount of *Love, Haha, Wow, Sad* and *Angry* emojis, respectively, and a multiple linear regression model for testing the *H1*(*a–c*) is as follows;

$$Response = \beta_0 + \beta_1 {*} LoveEmoji + \beta_2 {*} HahaEmoji + \beta_3 {*} WowEmoji + \beta_4 {*} SadEmoji + \beta_5 {*} AngryEmoji$$

Here, the *Response* is the dependent variable and, depending on the hypothesis, it is a number of *likes* – a variable that measures favoritism (*H1a*), *comments* – a variable that measures conversation (*H1b*) or *shares* – a variable that measures amplification (*H1c*). The list of test outcomes from the regression model, i.e. coefficient estimates (betas) along with *SE* (*standard error*), *t* and *p*-values are provided in Tables 5–7.

According to Table 5(a), which presents the results for Trump's page, the dependent variable *Number of Likes* is regressed on five independent variables. The LoveEmoji coefficient is 1.35, with a remarkably low *p*-value of 1.51e-8, indicating high statistical

Independent variables	Coefficient	Dependent variable: number of likes SE	*t*	*p*
a) *H1a* for Trump's page				
LoveEmoji	1.3484	0.2362	5.708	1.51e-8***
HaHaEmoji	3.4485	0.6486	5.317	1.3e-7***
WowEmoji	−5.9540	6.4513	−0.923	0.356
SadEmoji	2.6847	3.5837	0.749	0.454
AngryEmoji	1.1034	0.9312	1.185	0.236
b) *H1a* for Clinton's page				
LoveEmoji	3.4019	0.1231	27.645	<2e-16***
HaHaEmoji	4.6003	0.7134	6.449	1.61e-10***
WowEmoji	11.2541	2.2788	4.939	8.94e-7***
SadEmoji	5.2400	0.5739	9.130	<2e-16***
AngryEmoji	−1.3016	0.6021	−2.162	0.0308*

Notes: $R^2 = 0.11$; adjusted $R^2 = 0.1055$; $R^2 = 0.5371$; adjusted $R^2 = 0.5353$; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Table 5.
Multiple linear regression results for favoritism (*H1a*)

significance. Similarly, the HaHaEmoji coefficient is 3.45, with a highly significant p-value of 1.3e-7. However, based on their p-values, WowEmoji, SadEmoji and AngryEmoji do not show a significant relationship with the number of likes.

The results from Table 5(b), which present the findings for Clinton's page, reveal significant coefficients for various emojis. The LoveEmoji coefficient is 3.4, with an extremely low p-value of <2e-16, indicating high statistical significance. Similarly, the HaHaEmoji coefficient stands at 4.6, with a highly significant p-value of 1.61e-10. The WowEmoji coefficient shows a substantial value of 11.25, also supported by a highly significant p-value of 8.94e-7. Furthermore, the SadEmoji coefficient is 5.24, with an extremely low p-value of <2e-16, suggesting a strong and significant relationship. However, the AngryEmoji coefficient displays a negative value of −1.3, indicating a significant relationship with the number of likes ($p < 0.05$).

The regression results indicate that the use of LoveEmoji and HaHaEmoji has a strong positive association with the number of likes on both Trump's and Clinton's pages, suggesting that posts containing these emojis tend to receive more likes. However, the WowEmoji and SadEmoji show no significant impact on likes for Trump's page, while it has a positive and significant effect on Clinton's page. The AngryEmoji shows no significant effect on Trump's page but has a significant negative effect on Clinton's page, implying that posts with AngryEmoji may receive fewer likes on her page.

According to the value of adjusted R^2 parameter in Table 5(a) and (b), considerably more variability in Clinton's model is explained by emotional variables than in Trump's, suggesting that emoji usage is a critical determinant of *likes* received. It implies that Trump's followers possibly experience a wider range of emotions than suggested by Facebook emojis or that factors beyond emoji usage play a more significant role in determining *likes*. There is much anticipation, trust, expectation and disappointment when watching political debates (Arash and Balaji, 2015) and given that Trump was not an active politician before his presidential candidacy, people obviously perceive him much differently than the familiar candidate (Bickart *et al.*, 2017).

Table 6(a) and (b) present the results of multiple linear regression for conversation (*H1b*). The dependent variable *Number of Comments* is regressed on five independent variables.

Independent variables	Coefficient	SE	t	p
	Dependent variable: number of comments			
a) *H1b* for Trump's page				
LoveEmoji	4.2192	0.1048	40.261	<2e-16***
HaHaEmoji	−1.0718	0.2877	−3.725	0.000206***
WowEmoji	−29.5624	2.8619	−10.329	<2e-16***
SadEmoji	3.8839	1.5898	2.443	0.014739*
AngryEmoji	10.2445	0.4131	24.800	<2e-16***
b) *H1b* for Clinton's page				
LoveEmoji	1.37767	0.04103	33.580	<2e-16***
HaHaEmoji	0.23008	0.23784	0.967	0.333534
WowEmoji	−6.73020	0.75977	−8.858	<2e-16***
SadEmoji	−2.62935	0.19135	−13.741	<2e-16***
AngryEmoji	3.95334	0.20073	19.695	<2e-16***

Notes: $R^2 = 0.8191$; adjusted $R^2 = 0.8182$; $R^2 = 0.55$; adjusted $R^2 = 0.5431$; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Table 6. Multiple linear regression results for conversation (*H1b*)

The statistical analysis of Trump's page reveals significant coefficients for LoveEmoji (4.22), HaHaEmoji (−1.07), WowEmoji (−29.56) and AngryEmoji (10.24). These coefficients show high statistical significance. Additionally, the SadEmoji coefficient of 3.88, with a *p*-value of 0.014739, indicates a meaningful relationship with the number of comments.

Clinton's page exhibits the following coefficients: LoveEmoji (1.38), WowEmoji (−6.73), SadEmoji (−2.63) and AngryEmoji (3.95). Each of these coefficients demonstrates a remarkably low *p*-value of <2e-16, indicating a strong and highly statistically significant relationship. However, it is worth noting that HaHaEmoji does not display any significant relationship with the number of comments.

According to the adjusted R^2 parameter in Table 6(a) and (b), considerably more variability the Trump's model is explained by emotional variables than in Clinton's. This indicates that people like to discuss any topic, positive or negative, relating to Trump's posting. Given that the maximum virality index is achieved in commenting on Trump's page [Table 1(a)], it seems that Trump's posts were more provocative than Clinton's, as writing opinion (commenting) is something people, in general, do less than liking or sharing on Facebook (Bickart *et al.*, 2017).

Table 7(a) and (b) present the results of multiple linear regression for amplification (*H1c*). The dependent variable *Number of Shares* is regressed on five independent variables.

On Trump's page, LoveEmoji and SadEmoji show no significant relationship with the number of shares. However, HaHaEmoji exhibits a coefficient of 6.73, accompanied by an extremely low *p*-value of <2e-16, signifying high statistical significance. Additionally, WowEmoji has a coefficient of 10.59, with a *p*-value of 0.000737, indicating high significance. Furthermore, AngryEmoji displays a coefficient of 1.69, with an extremely low *p*-value of 0.000178. The model's adjusted R-squared value is 0.4171, suggesting that approximately 41.71% of the variance in the number of shares can be explained by the independent variables in this analysis. These results highlight the notable impact of HaHaEmoji, WowEmoji and AngryEmoji on the sharing behavior of Trump's page content, while LoveEmoji and SadEmoji seem to have little to no influence on share count.

AngryEmoji on Clinton's page does not exhibit a significant relationship with the number of shares. However, the coefficients for other emojis show noteworthy patterns. LoveEmoji has a coefficient of 0.98, HaHaEmoji 2.52, WowEmoji 13.87 and SadEmoji

	Dependent variable: number of shares			
Independent variables	Coefficient	SE	*t*	*p*
a) *H1c* for Trump				
LoveEmoji	−0.08531	0.11460	−0.744	0.456823
HaHaEmoji	6.73339	0.31463	21.401	<2e-16***
WowEmoji	10.59683	3.12964	3.386	0.000737***
SadEmoji	−1.93210	1.73849	−1.111	0.266678
AngryEmoji	1.69985	0.45173	3.763	0.000178***
b) *H1c* for Clinton				
LoveEmoji	0.98457	0.08302	11.86	<2e-16***
HaHaEmoji	2.51588	0.48125	5.228	2.01e-7***
WowEmoji	13.8736	1.53736	9.024	<2e-16***
SadEmoji	8.35477	0.38719	21.578	<2e-16***
AngryEmoji	0.25577	0.40617	0.63	0.529

Notes: $R^2 = 0.42$; adjusted $R^2 = 0.4171$; $R^2 = 0.6431$; adjusted $R^2 = 0.6417$; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Table 7. Multiple linear regression results for amplification (*H1c*)

8.35477, all displaying extremely low p-values of <2e-16, signifying high statistical significance. The model's adjusted R-squared value is 0.6417, indicating that approximately 64.17% of the variance in the number of shares can be explained by the independent variables in this analysis. These findings underscore the substantial impact of certain emojis, particularly LoveEmoji, HaHaEmoji, WowEmoji and SadEmoji, on the sharing behavior of Clinton's page content.

Based on the regression results, it can be concluded that the impact of emojis on amplification varies between Trump's and Clinton's pages. These findings highlight the importance of using emojis strategically in social media communication to enhance amplification. For social media managers, understanding the differential impact of emojis on engagement metrics (likes, comments, shares) for different political figures can help optimize content creation and communication strategies. It is essential to leverage emojis that resonate well with the audience and encourage sharing behavior. However, considering other contextual factors and potential interactions between emojis and other content elements is crucial for a comprehensive understanding of social media engagement.

The results of valence, arousal and dominance analysis

Furthermore, an insight into the relationship between virality indices, and basic constituents of emotions is provided in this section. We perform a multiple linear regression with the set of predictor variables *Valence*, *Arousal* and *Dominance*, which represent the amount of these emotional constituents, respectively, and a model for testing *H2*(*a–c*) is as follows;

$$Response = \beta_0 + \beta_1 * Valence + \beta_2 * Arousal + \beta_3 * Dominance$$

The *Response* is the dependent variable and, depending on the hypothesis, it is a number of *likes* that measures favoritism (*H2a*), *comments* that measures conversation (*H2b*) or *shares* that measures amplification (*H2c*). The list of test outcomes from the regression model, i.e. coefficient estimates (betas) along with *SE* (*standard error*), t and p-values are provided in Tables 8–10.

It can be observed from Table 8(a) that all emotional constituents are significant predictors for the number of likes on Trump's page, with positive coefficient estimates for valence (0.042) and arousal (0.058) and negative for dominance (−0.098), indicating that less dominant content, with high arousal and more positive emotions, is more viral. This finding extends Berger and Milkman's (2012) finding of more positive content with high arousal and confirms our finding from the previous section on Trump's posts.

According to Table 8(b), on Clinton's page valence (with a coefficient of 0.042) is a significant predictor of favoritism, i.e. more positive content is more viral, which is in line with Berger and Milkman's (2012) finding of positive content but restricts our finding from the previous section for Clinton's posts. However, this finding confirms an overall implication that Clinton had a less provocative election strategy on social media. It is expected since the followers of both candidates differ (Lacatus and Meibauer, 2021).

It is interesting to observe how commenting and sharing (Tables 9 and 10) relate to each other in terms of valence, arousal and dominance. On Trump's page, these are in accordance with Guerini and Staiano (2015) finding that conversation and amplification have opposing roles. More specifically, Trump's supporters turn to comment when they feel more arousal [Table 9(a)], and they turn to share when they feel less arousal [Table 10(a)]. In addition, according to dominance, they turn to share when they feel more in control or when they experience more negative emotions.

Table 8.
Multiple linear regression results for favoritism (*H2a*)

	Dependent variable: number of likes			
Independent variables	Coefficient	SE	t	p
a) *H2a* for Trump's page				
Valence	0.04190	0.01167	3.589	0.000349***
Arousal	0.05847	0.02241	2.609	0.009239**
Dominance	−0.09890	0.02915	−3.393	0.000720***
b) *H2a* for Clinton's page				
Valence	0.04193	0.00750	5.591	2.89e-8***
Arousal	−0.02105	0.01651	−1.274	0.203
Dominance	−0.01421	0.01872	−0.759	0.448

Notes: R^2 = 0.01437; adjusted R^2 = 0.01115; R^2 = 0.135; adjusted R^2 = 0.1325; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Table 9.
Multiple linear regression results for conversation (*H2b*)

	Dependent variable: number of comments			
Independent variables	Coefficient	SE	t	p
a) *H2b* for Trump's page				
Valence	−0.007475	0.095520	−0.792	0.428814
Arousal	−0.066967	0.018131	−3.693	0.000234***
Dominance	0.033727	0.023577	1.430	0.152919
b) *H2b* for Clinton's page				
Valence	−0.017541	0.005419	−3.237	0.00125**
Arousal	0.010741	0.011932	0.900	0.36822
Dominance	0.008412	0.013528	0.622	0.53418

Notes: R^2 = 0.0207; adjusted R^2 = 0.01751; R^2 = 0.1432; adjusted R^2 = 0.1353; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Table 10.
Multiple linear regression results for amplification (*H2c*)

	Dependent variable: number of shares			
Independent variables	Coefficient	SE	t	p
a) *H2c* for Trump's page				
Valence	−0.03442	0.08244	−4.224	2.64e-5***
Arousal	0.00850	0.00815	0.543	0.58711
Dominance	0.06518	0.02035	3.203	0.00141**
b) *H2c* for Clinton's page				
Valence	−0.024392	0.006497	−3.754	0.000183***
Arousal	0.010307	0.014306	0.720	0.471426
Dominance	0.005800	0.016220	0.358	0.720736

Notes: R^2 = 0.01596; adjusted R^2 = 0.0134; R^2 = 0.06908; adjusted R^2 = 0.06639; significance codes: 0 *** 0.001 ** 0.01 * 0.05°
Source: Table by the author

Considering Clinton's supporters, only valence is a significant predictor for commenting and sharing [Tables 9(b) and 10(b)] with negative coefficient estimates (−0.0175). This aligns with findings from the previous section that both positive and negative emotions with low arousal influence virality on a Clinton page, which contrasts with Berger and Milkman's (2012) finding of positive content with high arousal and virality. It seems again that Clinton's posts were less provocative than Trump's.

In answer to *RQ3*, *H2*(*a–c*) for Trump's and Clinton's pages are confirmed, indicating that certain users' reactions are influenced by *how* events are presented on Facebook and *what* is written about them. More in-depth analysis may reveal more subtle differences of Trump and Clinton followers (Lacatus, 2021).

Discussion

Conclusions

According to Schill and Hendricks (2018), "a single issue didn't determine the election outcome; instead, a multidimensional constellation of factors was at work, of which social media was a bright star." Trump's Electoral College victory can be seen as a "culminating event of Americans' distrust of government and media institutions, anxiety towards economic and cultural change in the country, and partisan sorting and polarization." Clinton outpaced Trump by almost 2.9 million voters, yet loses the Electoral College by significant margins, so she plainly made strategic and tactical mistakes (Ball, 2016).

The results from this study suggest that much success of an election campaign lies in presenting the frames around the events, i.e. in choosing whether to present an event as positive, negative or where to put focus. Based on our data set statistics (Tables 2 and 3), it seems that Trump has been a front-runner on Facebook and given an emotional proportion overview of Trump's and Clinton's pages (Figures 3 and 4), it seems that Trump has tended to skew his messages in a positive way, as a study of Skaperdas and Grofman (1995) showed for a two-candidate election.

The regression results from Table 5(a) and (b) suggest that the use of *Love* and *HaHa* emojis positively influences the number of likes on both Trump's and Clinton's pages. For Clinton's page, the *Wow* emoji has a significant positive effect, while the *Angry* emoji has a significant negative effect. Favoritism for Trump's page is in accordance with Berger and Milkman (2012) finding that positive content is more viral than negative content. For Clinton's page, it seems that both positive and negative content are equally viral, which contrasts Berger and Milkman (2012) findings of positive content and virality.

According to Table 6(a) and (b), the number of user comments is significantly influenced by all emotional dimensions, except that *funny* content on Clinton's page does not have a significant effect on user commenting. This means that for both candidates, positive and negative content influence virality, which contrasts Berger and Milkman (2012) finding that positive content is more viral than negative content. In addition, it can be noticed that the two pages differ in the coefficient estimates for the *sad* emotion, i.e. the coefficient is positive on Trump's page and negative on Clinton's page, which means that Trump's *sad* posts are proportional to the conversation, while Clinton's *sad* posts are reverse proportional to the conversation. This means that *sad* users write what makes them *sad* on Trump's page, but *sad* users do not write much about what makes them *sad* on Clinton's page. However, given that *sad* emotion has low arousal, and *anger* has high arousal (Warriner *et al.*, 2013), Clinton's page still confirms Berger and Milkman (2012) finding.

Furthermore, Table 7(a) shows that amplification is influenced by the *Haha*, *Wow* and *Angry* emotions, and not by *Love* and *Sad* emotion on Trump's page, which means that followers mostly share positive content, or the content that makes them *angry*, which is in line with both Berger and Milkman's (2012) finding of a relationship between emotion and social transmission that "content that evokes either positive or negative emotions characterized by high arousal is more viral." On the other side, Clinton's followers share any content that does not make them *angry* [Table 7(b)], which contrasts both Berger and Milkman (2012) findings on the relationship between emotion and social transmission.

Overall, Trump's supporters made more viral content with *hard* emotions (*Haha*, *Angry* and *Wow*), while Clinton's supporters made more viral content with *soft* emotions (*Love* and *Sad*). However, it should be noted that emojis are not designed to capture the full range of human emotions, which implies certain limitations of emojis to identify the positive or negative characteristics in the candidates' campaigns, i.e. there might be latent positive or negative reactions to both candidates and their posts.

According to the performed VAD analysis (Tables 8–10), favoritism, conversation and amplification on Clinton's page have only been influenced by valence, i.e. her supporters liked more positive content; however, they commented and shared more negative content. On Trump's page, favoritism, conversation and amplification have been more influenced by other constituents of emotions than valence, i.e. his supporters liked and commented on the content with more arousal and shared more negative and dominant content. This indicates that Trump's social media campaign focused more on *hard* emotions (Sanford, 2007).

Complementing the VAD with emotion analysis, it seems that Trump's posts evoked much more *hard* emotions than Clinton's, which leads to the conclusion that Trump's social media campaign strategy can be called *hard*, while Clinton's is consequently *soft*. Based on this assumption, we confirm the finding of Harrington and Hess (1996) that a stronger candidate (i.e. Trump) engages in a rather positive campaign, as well as the finding of Gregory (2015) that a positive campaign is more effective than its counterparts.

Practical and theoretical implications

By unraveling the emotional dimensions and engagement patterns on Facebook, the study informs political campaigns about the types of content and emotions that resonate with their followers. In turn, this knowledge can be used to develop more effective social media strategies, foster voter engagement and enhance democratic discourse during future elections. By examining the relationships between emotions and user engagement metrics, this understanding can help political campaigns tailor their social media content to encourage specific types of engagement from their target audience.

The study's use of regression models to analyze emotional reactions provides a comprehensive understanding of emotions beyond simply positive and negative categories. This nuanced approach to emotions helps identify the specific emotional content that resonates with each candidate's audience. Such insights can inform the creation of emotionally impactful content that aligns with the candidates' political messaging.

Understanding how emotions influence user reactions on these platforms is crucial for fostering healthy democratic discourse. By analyzing the emotional reactions to candidates' posts, political campaigns can gain insights into the sentiments and concerns of the electorate, enabling them to address issues that matter to the voters effectively. However, it is important to consider that other factors not included in this model may also play a role in shaping user engagement on social media platforms. Further research is needed to explore additional variables and potential causality in these relationships.

Limitations and future work

Social media have faced some pressure from consumers and civil society to reduce the prevalence of fake news on their systems (Allcott and Gentzkow, 2017). For instance, Facebook is removing fake news sites from its advertising platforms on the grounds that they violate policies against misleading content (Wingfield *et al.*, 2016). So, the limitation of this research to be more explored is the influence of fake news, which might affect the research results (Cvitanović and Bagić Babac, 2022).

Although our conclusions are based on one of the most important political events of 2016, our data set is still limited to only two Facebook pages, so further exploration is needed with data from other social media websites such as Twitter, Instagram, etc., to extend our analysis to a larger scale and to get more generalized conclusions.

Furthermore, the VAD analysis in this study is based on mapping Facebook emojis to words, so these emojis might be interpreted differently depending on the semantics of chosen words. It should be explored how different interpretations of emojis are reflected in the same data set, and in the regression models. Also, the used emotional circumplex could be extended beyond the scope of five Facebook emojis to a wider range of emotional dimensions for a more extensive analysis.

Another limitation of this study is the potential lack of recognition of posttrolling and its corresponding responses. This absence of clear guidelines may lead to a skewed interpretation of the results. Future research should consider incorporating measures or strategies to identify and distinguish trolling behavior and responses to enhance the accuracy and validity of the findings.

Future work should address the implications of Trump's *hard* communication strategy for political marketing and the economy; "as 2016 has proven, we're in a new branding world" (Bickart *et al.*, 2017) using advanced computational techniques in natural language processing (Brzić *et al.*, 2023) and machine learning (Marijić and Bagić Babac, 2023).

References

Alashri, S., Kandala, S.S., Bajaj, V., Ravi, R., Smith, K.L. and Desouza, K.C. (2016), "An analysis of sentiments on Facebook during the 2016 U.S. Presidential election", *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*,

Allcott, H. and Gentzkow, M. (2017), "Social media and fake news in the 2016 election", *Journal of Economic Perspectives*, Vol. 31 No. 2, pp. 211-236.

Almasy, S. (2016), "Muhammad Ali 'the greatest,' dies at 74", Madison Park and Joe Sutton, CNN, available at: http://edition.cnn.com/2016/06/03/us/muhammad-ali/ (accessed April 23).

Aragón, G.A. (2016), "A review in campaigns: going positive and negative", Trends in Mathematical Economics, pp. 35-41.

Arash, B. and Balaji, P. (2015), "Does television viewership predict presidential election outcomes?", *Big Data*, Vol. 3 No. 3, pp. 138-147.

Bagić Babac, M. (2023), "Emotion analysis of user reactions to online news", *Information Discovery and Delivery*, Vol. 51 No. 2, pp. 179-193, doi: 10.1108/IDD-04-2022-0027.

Bagić Babac, M. and Podobnik, V. (2023), "World-class sporting events as arenas of emotional eruptions on social media", *Soccer and Society (to Appear)*, doi: 10.1080/14660970.2023.2229743.

Bagić Babac, M. and Podobnik, V. (2018), "What social media activities reveal about election results? The use of Facebook during the 2015 general election campaign in Croatia", *Information Technology and People*, Vol. 31 No. 2, pp. 327-347.

Ball, M. (2016), "Why Hillary Clinton lost", Atlantic, available at: www.theatlantic.com/politics/archive/2016/11/why-hillary-clinton-lost/507704/

Bazarova, N.N., Choi, Y.H., Sosik, V.S., Cosley, D. and Whitlock, J. (2015), "Social sharing of emotions on Facebook: channel differences, satisfaction, and replies", *Cscw*, pp. 14-18. Vancouver, BC, Canada.

Bene, M. (2017), "Sharing is caring! Investigating viral posts on politicians' Facebook pages during the 2014 general election campaign in Hungary", *Journal of Information Technology and Politics*, Vol. 14 No. 4, pp. 387-402.

Berger, J. and Milkman, K. (2012), "What makes online content viral?", *Journal of Marketing Research*, Vol. 49 No. 2, pp. 192-205.

Bickart, B., Fournier, S. and Nisenholtz, M. (2017), "What Trump understands about using social media to drive attention", *Harvard Business Review*, available at: https://hbr.org/2017/03/what-trump-understands-about-using-social-media-to-drive-attention (accessed April 14 2017).

Borah, P. (2016), "Political Facebook use: Campaign strategies used in 2008 and 2012 presidential elections", *Journal of Information Technology and Politics*, Vol. 13 No. 4, pp. 326-338.

Bradley, M.M. and Lang, P.J. (1994), "Measuring emotion: the self-assessment manikin and the semantic differential", *Journal of Behavior Therapy and Experimental Psychiatry*, Vol. 25 No. 1, pp. 49-59.

Bronstein, J. (2013), "Like me! Analyzing the 2012 presidential candidates' Facebook pages", *Online Information Review*, Vol. 37 No. 2, pp. 173-192.

Brzić, B., Botički, I. and Amd Bagić Babac, M. (2023), "Detecting deception using natural language processing and machine learning in datasets on COVID-19 and climate change", *Algorithms*, Vol. 16 No. 221, doi: 10.3390/a16050221.

Campani, G., Fabelo Concepción, S., Rodriguez Soler, A. and Sánchez Savín, C. (2022), "The rise of Donald Trump Right-Wing populism in the United States: middle American radicalism and anti-Immigration discourse", *Societies*, Vol. 12 No. 6, p. 154, doi: 10.3390/soc12060154.

Christensen, A. (2000), *Reconcilable Differences*, The Guilford Press, New York, NY.

Cogburn, D.L. and Espinoza-Vasquez, F.K. (2011), "From networked nominee to networked nation: examining the impact of web 2.0 and social media on political participation and civic engagement in the 2008 Obama campaign", *Journal of Political Marketing*, Vol. 10 Nos 1/2, pp. 189-213.

Cvitanović, I. and Bagić Babac, M. (2022), "Deep learning with Self-Attention mechanism for fake news detection", in Lahby, M., Pathan, A.S.K., Maleh, Y. and Yafooz, W.M.S. (Eds), *Combating Fake News with Computational Intelligence Techniques*, Springer, Switzerland, pp. 205-229, doi: 10.1007/978-3-030-90087-8_10.

Dang-Xuan, L., Stieglitz, S., Wladarsch, J. and Neuberger, C. (2013), "An investigation of influentials and the role of sentiment in political communication on Twitter during election periods", *Information, Communication and Society*, Vol. 16 No. 5, pp. 795-825.

Edgerly, S., Thorson, K., Bighash, L. and Hannah, M. (2016), "Posting about politics: media as resources for political expression on Facebook", *Journal of Information Technology and Politics*, Vol. 13 No. 2, pp. 108-125.

Ekman, P. (1992), "An argument for basic emotions", *Cognition and Emotion*, Vol. 6 Nos 3/4, pp. 169-200.

Enli, G. (2017), "Twitter as arena for the authentic outsider: exploring the social media campaigns of Trump and Clinton in the 2016 US presidential election", *European Journal of Communication*, Vol. 32 No. 1, pp. 50-61.

Gainous, J. and Wagner, K.M. (2013), "Tweeting to power: the social media revolution in American politics", *Oxford Studies in Digital Politics*.

Gerodimos, R. and Justinussen, J. (2015), "Obama's 2012 Facebook campaign: political communication in the age of the like button", *Journal of Information Technology and Politics*, Vol. 12 No. 2, pp. 113-132.

Grčić, K., Bagić Babac, M., V. and Podobnik, V. (2017), "Generating politician profiles based on content analysis of social network datasets", *Journal of Universal Computer Science*, Vol. 23 No. 3, pp. 236-255.

Gregory, P.A. (2015), "Comparing the effectiveness of positive and negative political campaigns", *Political Science*, Vol. 7 No. 11, p. 2.

Guerini, M. and Staiano, J. (2015), "Deep feelings: a massive cross-lingual study on the relation between emotions and Virality", *Proceedings of the 24th International Conference on World Wide Web (WWW '15)*. ACM, New York, NY, pp. 299-305.

Harrington, J.E. and Hess, G.D. (1996), "A spatial theory of positive and negative campaigning", *Games and Economic Behavior*, Vol. 17 No. 2, pp. 209-229.

Heiss, R., Schmuck, D. and Matthes, J. (2018), "What drives interaction in political actors' Facebook posts? Profile and content predictors of user engagement and political actors' reactions", *Information, Communication and Society*, Vol. 22 No. 10.

Hong, S. and Nadler, D. (2011), "Does the early bird move the polls? The use of the social media tool 'twitter' by U.S. politicians and its impact on public opinion", *Proceedings of the 2011 International Conference on Digital Government Research*.

Johnson, T.J. and Kaye, B.K. (2003), "A boost or bust for democracy? How the web influenced political behaviors in the 1996 and 2000 presidential elections", *Harvard International Journal of Press/Politics*, Vol. 8 No. 3, pp. 9-34.

Kralj Novak, P., Smailović, J., Sluban, B. and Mozetič, I. (2015), "Sentiment of emojis", *Plos One*, Vol. 10 No. 12, p. e0144296.

Lacatus, C. (2021), "Populism and President Trump's approach to foreign policy: an analysis of tweets and rally speeches", *Politics*, Vol. 41 No. 1, pp. 31-47.

Lacatus, C. and Meibauer, G. (2021), "Introduction to the special issue: elections, rhetoric and American foreign policy in the age of Donald Trump", *Politics*, Vol. 41 No. 1, pp. 3-14.

Larsson, A.O. (2017), "Going viral? Comparing parties on social media during the 2014 Swedish election", *Convergence: The International Journal of Research into New Media Technologies*, Vol. 23 No. 2, pp. 117-131.

Lee, T. (2019), "The global rise of 'fake news' and the threat to democratic elections in the USA", *Public Administration and Policy*, Vol. 22 No. 1, pp. 15-24.

Lilleker, D.G. and Jackson, N.A. (2011), *Political Campaigning, Elections and the Internet*, Routledge, London.

Lin, R. and Utz, S. (2015), "The emotional responses of browsing Facebook: happiness, envy, and the role of tie strength", *Computers in Human Behavior*, Vol. 52, pp. 29-38.

Luminet, O., Bouts, P., Delie, F., Manstead, A.S. and Rimé, B. (2000), "Social sharing of emotion following exposure to a negatively Valenced situation", *Cognition and Emotion*, Vol. 14 No. 5, pp. 661-688.

Marijić, A. and Bagić Babac, M. (2023), "Predicting song genre with deep learning", *Global Knowledge, Memory and Communication*, doi: 10.1108/GKMC-08-2022-0187.

Mohammad, S.M., Zhu, X., Kiritchenko, S. and Martin, J. (2014), "Sentiment, emotion, purpose, and style in electoral tweets", *Information Processing and Management*, Vol. 51 No. 4, pp. 480-499.

Mutz, D.C. and Martin, P.S. (2001), "Facilitating communication across lines of political difference: the role of mass media", *American Political Science Review*, Vol. 95 No. 1, pp. 97-114.

Oliveira, D.J.S., de Souza Bermejo, P.H. and dos Santos, P.A. (2017), "Can social media reveal the preferences of voters? A comparison between sentiment analysis and traditional opinion polls", *Journal of Information Technology and Politics*, Vol. 14 No. 1, pp. 34-45.

Peters, K., Kashima, Y. and Clark, A. (2009), "Talking about others: emotionality and the dissemination of social information", *European Journal of Social Psychology*, Vol. 39 No. 2, pp. 207-222.

Plutchik, R. (1980), *Emotions: A Psychoevolutionary Synthesis*, Harper and Row, New York, NY.

Powell, G.N., Butterfield, D.A. and Jiang, X. (2018), "Why Trump and Clinton won and lost: the roles of hypermasculinity and androgyny", *Equality, Diversity and Inclusion: An International Journal*, Vol. 37 No. 1, pp. 44-62.

Puh, K. and Bagić Babac, M. (2023), "Predicting sentiment and rating of tourist reviews using machine learning", *Journal of Hospitality and Tourism Insights*, Vol. 6 No. 3, pp. 1188-1204, doi: 10.1108/JHTI-02-2022-0078.

Reevy, G.M., Ozer, Y.M. and Ito, Y. (2010), *Encyclopedia of Emotion*, Greenwood Publishing Group, Oxford, Vol. 1.

Russell, J.A. (1980), "A circumplex model of affect", *Journal of Personality and Social Psychology*, Vol. 39 No. 6, p. 1161.

Sahly, A., Shao, C. and Kwon, K.H. (2019), "Social media for political campaigns: an examination of Trump's and Clinton's frame building and its effect on audience engagement", *Social Media + Society*, Vol. 5 No. 2, pp. 1-13.

Samuel-Azran, T., Yarchi, M. and Wolfsfeld, G. (2015), "Equalization versus normalization: Facebook and the 2013 Israeli elections", *Social Media + Society*, Vol. 1 No. 2, pp. 1-9.

Sandoval-Almazan, R. and Valle-Cruz, D. (2020), "Sentiment analysis of Facebook users reacting to political campaign posts", *Digital Government: Research and Practice*, Vol. 1 No. 2, p. 12.

Sanford, K. (2007), "Hard and soft emotion during conflict: investigating married couples and other relationships", *Personal Relationships*, Vol. 14 No. 1, pp. 65-90.

Schill, D. and Hendricks, J.A. (2018), "Discourse, disruption, and digital democracy: political communication in the 2016 presidential campaign", *The Presidency and Social Media*, Routledge, New York, NY, pp. 3-36.

Skaperdas, S. and Grofman, B. (1995), "Modeling negative campaigning", *American Political Science Review*, Vol. 89 No. 1, pp. 49-61.

Staiano, J. and Guerini, M. (2014), "DepecheMood: a lexicon for emotion analysis from Crowd-Annotated news", *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics*, *Baltimore, MD*, 23-25 June, pp. 427-433.

Steenkamp, M. and Hyde-Clarke, N. (2014), "The use of Facebook for political commentary in South Africa", *Telematics and Informatics*, Vol. 31 No. 1, pp. 91-97.

Tian, Y., Galery, T., Dulcinati, G., Molimpakis, E. and Sun, C. (2017), "Facebook sentiment: reactions and emojis", *Proceedings of the Fifth International Workshop on Natural Language Processing for Social Media*, pp. 11-16.

Tumasjan, A., Sprenger, T.O., Sandner, P.G. and Welpe, I.M. (2011), "Election forecasts with Twitter: how 140 characters reflect the political landscape", *Social Science Computer Review*, Vol. 29 No. 4, pp. 402-418.

Van Steenburg, E. and Guzmán, F. (2019), "The influence of political candidate brands during the 2012 and 2016 US presidential elections", *European Journal of Marketing*, Vol. 53 No. 12, pp. 2629-2656.

Warriner, A.B., Kuperman, V. and Brysbaert, M. (2013), "Norms of valence, arousal, and dominance for 13,915 English lemmas", *Behavior Research Methods*, Vol. 45 No. 4, pp. 1191-1207.

Wingfield, N., Isaac, M. and Benner, K. (2016), "Google and Facebook take aim at fake news sites", *New York Times*, 14 November.

Woolley, J.K., Limperos, A.M. and Oliver, M.B. (2010), "The 2008 presidential election, 2.0: a content analysis of user-generated political Facebook groups", *Mass Communication and Society*, Vol. 13 No. 5, pp. 631-652.

Xenos, M.A., Macafee, T. and Pole, A. (2017), "Understanding variations in user response to social media campaigns: a study of Facebook posts in the 2010 US elections", *New Media and Society*, Vol. 19 No. 6, pp. 826-842.

Young, L. and Soroka, S. (2012), "Affective news: the automated coding of sentiment in political texts", *Political Communication*, Vol. 29 No. 2, pp. 205-231.

Zech, E., Rimé, B. and Nils, F. (2004), "Social sharing of emotion, emotional recovery, and interpersonal aspects", The Regulation of Emotion, pp. 157-185.

Further reading

Bene, M. (2018), "Post shared, vote shared: Investigating the link between Facebook performance and electoral success during the Hungarian general election campaign of 2014", *Journalism and Mass Communication Quarterly*, Vol. 95 No. 2, pp. 363-380.

Berger, J. and Milkman, K. (2017), "Social transmission, emotion, and the virality of online content", Working paper, Marketing Science Institute, pp. 10-114, available at: www.msi.org/reports/social-transmission-emotion-and-the-virality-of-online-content/ (accessed 23 February 2017).

Blumler, J.G. and Kavanagh, D. (1999), "The third age of political communication", *Political Communication*, Vol. 16 No. 3, pp. 209-230.

Davis, J. (2017), "Presidential Campaigns and social networks: How Clinton and Trump used Facebook and Twitter during the 2016 Election", Senior Theses, No. 75, doi: 10.33015/dominican.edu/2017.POL.ST.01

Hansen, L.K., Arvidsson, A., Nielsen, F.A., Colleoni, E. and Etter, M. (2011), "Good friends, bad news – affect and Virality in Twitter", in Park, J.J., Yang, L.T. and Lee, C. (Eds), *Future Information Technology Communications in Computer and Information Science*, Springer, Berlin, Heidelberg, p. 185.

Hendricks, J.A. and Schill, D. (2017), "The social media election of 2016", *The 2016 US Presidential Campaign*, Palgrave Macmillan, Cham, pp. 121-150.

Liu, B. (2015), *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*, Cambridge University Press, Cambridge.

Morgan, S.L. and Lee, J. (2018), "Trump voters and the white working class", *Sociological Science*, Vol. 5, pp. 234-245.

Rimé, B., Mesquita, B., Boca, S. and Philippot, P. (1991), "Beyond the emotional event: six studies on the social sharing of emotion", *Cognition and Emotion*, Vol. 5 Nos 5/6, pp. 435-465.

Stieglitz, S. and Dang-Xuan, L. (2012), "Social media and political communication – a social media analytics framework", *Social Network Analysis and Mining*, Springer, Berlin, Heidelberg, doi: 10.1007/s13278-012-0079-3.

Williams, C.B. and Gulati, G. (2013), "Social networks in political campaigns: Facebook and the congressional elections of 2006 and 2008", *New Media and Society*, Vol. 15 No. 1, pp. 52-71.

Corresponding author
Marina Bagić Babac can be contacted at: marina.bagic@fer.hr