What Emotions Spread on Social Media? Examining Emotional Expression and Message Diffusion on Twitter during the 2018 US Mid-term Elections

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INTRODUCTION

- Social media platforms like Twitter have become influential players in the political world (Krishnadev, 2016). Campaigns for government leadership now rely on social media to get elected.
- While a large body of psychological research has identified politicians' social media preferences, little is known about which psychological factors drive their messages to be disseminated on such sites.
- Previous research indicates that emotional expressions are ubiquitous on social media (e.g., Hasell & Weeks, 2016; Dang-Xuan, Stieglitz, Wladarsch, & Neuberger, 2013). Particularly during election seasons, candidates frequently speak in emotional terms or use voter-energised content to try and mobilise voters.
- But what kinds of emotional expressions on Twitter capture the public's attention and influence the spread of a candidate's messages?
- The current research aims to shed light on the emotional factors that drive political information spreading online.
- Previous research on the topic has taken a valenced-based approach, revealing a positive-negative asymmetry in which negative information weighs more heavily than positive (Dang-Xuan et al., 2013), with fewer studies looking at message spreading containing specific emotions.
- Emotions of the same valence, such as anger, sadness, or fear elicit different behavioural responses (Lerner, Li, Valdesolo, & Kassam, 2015; see Frijda, 1986). Especially in the case of negative traits, certain types of emotions may elicit an approach orientation, while others may indicate an avoidance response making it important to disentangle the role of these (e.g., Carver & Harmon-Jones, 2009).

OBJECTIVES

- The present work goes beyond mere valence to examine multidimensional discrete emotions on message dissemination online.
- We do so by leveraging a dataset involving over 14,000 original tweets from both Democratic and Republican senate candidates over 9 weeks around the 2018 US midterm election period (09 October – 04 December, 2018).
- Controlling for external factors such as the number of followers and friends, and the time that politicians post the tweets, we examine a) what specific emotions those tweets relate to Democratic and Republican candidate, and b) exploring which kind of emotionally charged messages (i.e., joy, anger, fear, sadness and confidence) are more likely to spread (i.e., retweeted) from both sides, respectively.

METHOD

Dataset

- We employed a dataset examining original tweets (N = 14,252) posted by 79 US politicians from the two major political parties (Democrats and Republicans) over 9 weeks around the elections.
- We included an examination of Twitter messages for 79 Twitter users, including senate candidates and the important politicians not necessarily directly participating in the election (e.g., Donald Trump, Mike Pence, speaker of the US House of representatives, US Senate and House majority/minority leaders, and the official accounts of the two major US political parties on Twitter). The dataset was retrieved using Python with Tweepy API.

Tweets & Retweets

- In the current work, we measure retweeting behaviour, representing each retweet as a directed edge from the user who posted the original tweet to the user who made the retweet (Sainudiin, Yogeeswaran, Nash, & Sahioun, 2019).

Tweets & Retweets

Figure 1 presents a general overview of the volume of tweets and retweets employed by senators and prominent politicians over nine weeks around the 2018 US midterm election. Overall, the sample shows that Democrats tweeted 6,845 times, with Republicans tweeting 7,352 times.

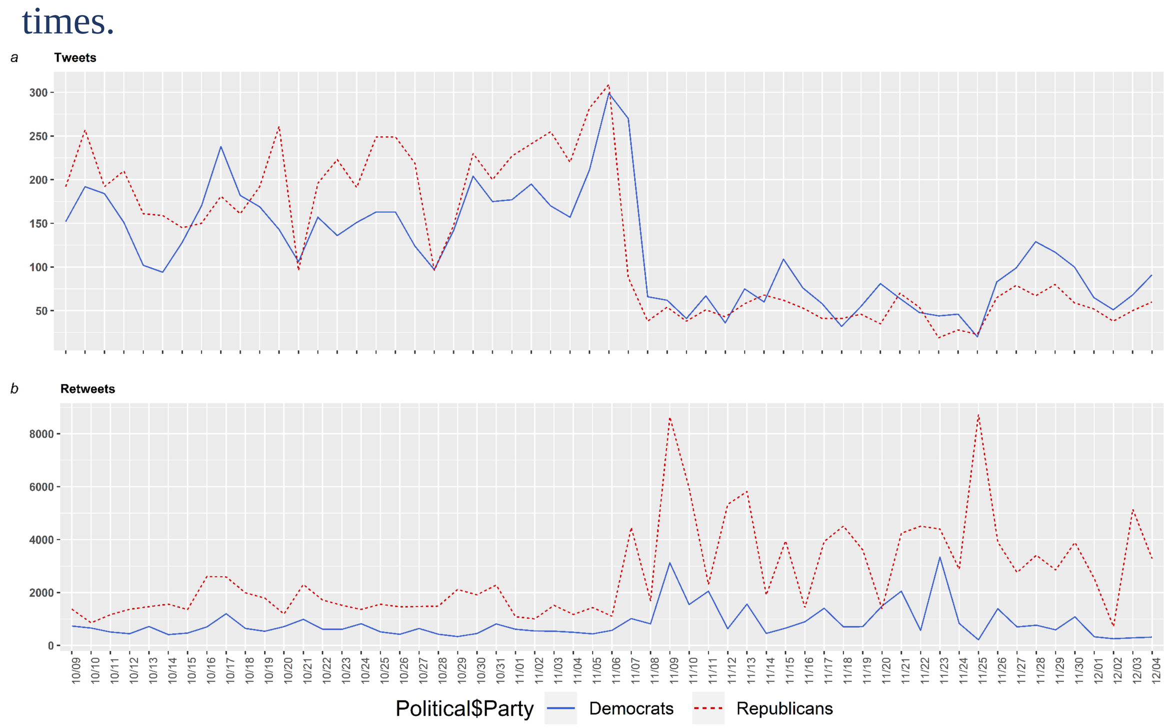

FIG. 1. AVERAGE DAILY VOLUME OF (A) TWEETS AND (B) RETWEETS OVER 9 WEEKS AROUND THE 2018 US MIDTERM ELECTIONS

Pre-Processing

Unlike emotion expressed in other textual sources, twitter messages firstly utilise a high number of colloquialisms and symbols such as URL links, repetition of letters and special characters. In order to convey twitter data in a way that increases the accuracy of the classifier in sentimental analysis, we conducted pre-processing using the following rules:

TABLE 1. PRE-PROCESSING ANALYSES FOR TEXT CLEANING

	Text Cleaning	Descriptions
Original Tweets	*It was gooood to join @JCRCMINNDAK this week at the Humphrey Institute to honor my friend and mentor Vice President Walter Mondale for his important and historic work on the Camp David negotiations forty years ago. ???@larryrjacobs & amp; ??? ???@SteveHunegs & amp; ???* https://t.co/dZDLVjP9Xn	Original Tweet was sent by senator Amy Klobuchar at November 23, 2018.
URL links	*It was gooood to join @JCRCMINNDAK this week at the Humphrey Institute to honor my friend and mentor Vice President Walter Mondale for his important and historic work on the Camp David negotiations forty years ago. ???@larryrjacobs??? ???@SteveHunegs???*	Removing URLs and hyperlinks.
@username	*It was gooood to join this week at the Humphrey Institute to honor my friend and mentor Vice President Walter Mondale for his important and historic work on the Camp David negotiations forty years ago. ?????? ??????*	Removing @username.
Spelling correction	*It was good to join this week at the Humphrey Institute to honor my friend and mentor Vice President Walter Mondale for his important and historic work on the Camp David negotiations forty years ago. ?? ??*	Checking spelling errors with repeated characters such as 'goood' and changing to 'good'.

Text-Based Emotion Detection

The inherent nature of social media content makes the use of sentiment analysis a distinct challenge. We used IBM Watson Tone Analyzer to measure emotions and tones in what people write online, such as tweets or reviews, and ultimately to detect whether they are happy, sad, anger, confident or fear. The Tone Analyzer returns at least one label for each tweet (e.g., anger), with the score normalised to between 0.5 and 1 (extremely anger).

TABLE 2. TWEETS CLASSIFICATION BY IBM TONE ANALYZER

Joy	Confidence	Anger	Fear	Sadness	Tweets Scoring High in Joy
0.96	0.70	0.00	0.00	0.00	Very grateful for all of the incredible musicians who joined us yesterday in Irving for a night of voting and music. So many amazing people showing up for Texas. Thank you!
					Tweets Scoring High in Anger
0.00	0.00	0.67	0.00	0.00	It is a simple: Senator Heller is lying about his record of repeatedly opposing, attacking, and failing to stand up for protections for people with pre-existing conditions. #NVDebate
0.00	0.54	0.63	0.00	0.00	I don't agree with Nancy Pelosi's agenda, but this is absolutely the wrong way to express those disagreements. If you want to stop her policies, don't threaten her, VOTE! That's how we settle our differences.
					Tweets Scoring High in Fear
0.00	0.00	0.00	0.87	0.00	The President continues his assault on the constitutionally guaranteed right of a #freepress because he's afraid of being asked tough questions he doesn't have answers to. Every American should be worried about this authoritarian action.
0.00	0.00	0.00	0.54	0.53	The science is clear: Our climate is already changing. We cannot allow lawmakers to continue ignoring this reality. The threats are too severe the consequences too catastrophic. We must act now, while we still can.

RESULTS

Tweets and Emotional Content

- Figure 1 highlights the dispersal of emotional content in tweets. Although joy remains the leading emotion shown among both Democrats and Republicans (Democrats: 61.4%, N = 2,301; Republicans: 64.5%, N = 2,085), key distinctions become visible.
- Among Republicans, the tweet content also shows confidence 16.6% (N = 657) of the time, with sadness 14.9% (N = 594) of the time, and anger and fear least often (2.34%, N = 93 and 1.56%, N = 62, respectively).
- Looking at Democrats' tweets, sadness occurs quite often (19.1%, N = 718), followed by confidence (14.5%, N = 544). Both anger and fear were expressed at comparably low levels (3.08%, N = 116 and 2.07%, N = 78, respectively).

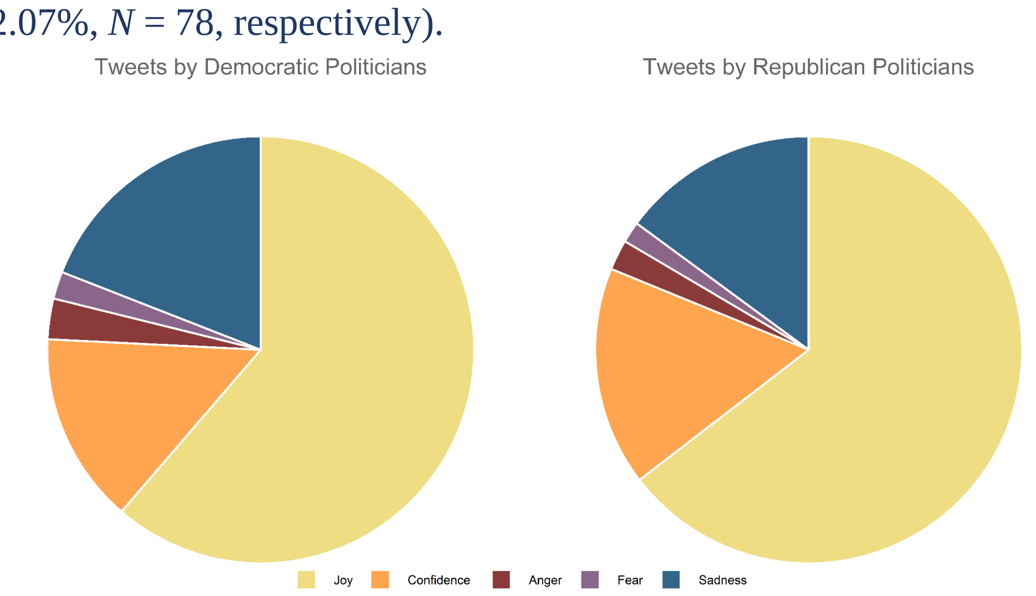

FIG. 2. DISTRIBUTION OF EMOTIONAL CONTENT IN TWEETS BY PERCENTAGE (%)

The Importance of Emotions in Message Dissemination

- Although messages with content in the anger category resulted in a plethora of retweeting activity by Republican followers ($\overline{RTs}_{anger}$ = 6,184, $\overline{RTs}_{fear}$ = 2,911, $\overline{RTs}_{sadness}$ = 2,570), fear was clearly the driving factor as far as Democrat followers were concerned ($\overline{RTs}_{fear}$ = 1,634, $\overline{RTs}_{anger}$ = 1,200, $\overline{RTs}_{sadness}$ = 818).
- In addition, unlike the tendency to respond to fear and anger, followers from both camps are relatively less motivated to respond to tweets expressing joy and confidence (Democrats: $\overline{RTs}_{joy}$ = 414, $\overline{RTs}_{confidence}$ = 671 ; Republicans: $\overline{RTs}_{joy}$ = 1,892, $\overline{RTs}_{confidence}$ = 2,109), regardless of there being a significant level of content expressing this emotion.

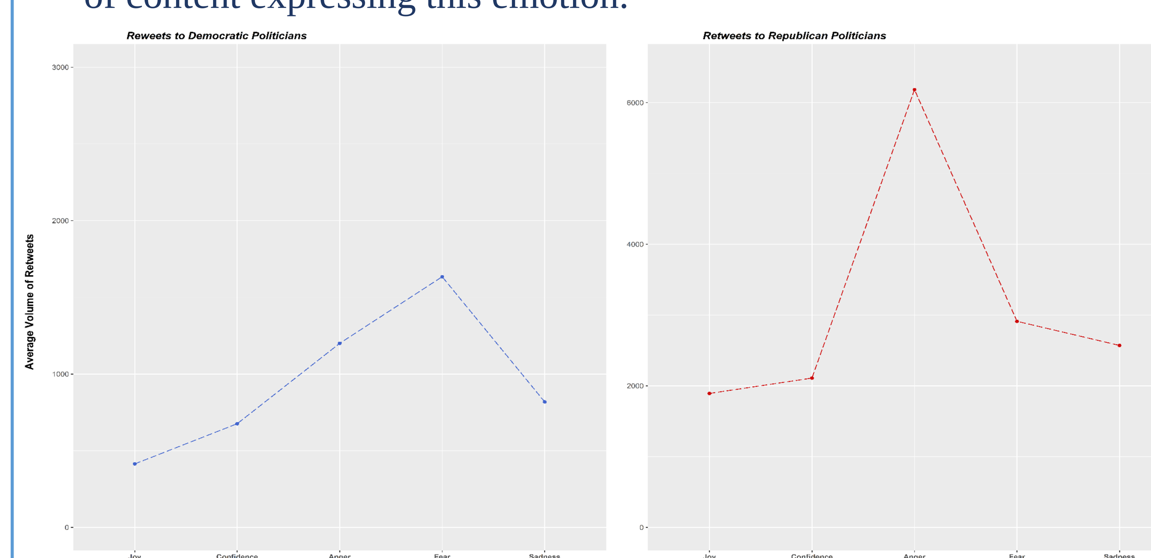

FIG. 3. DISTRIBUTION OF EMOTIONAL CONTENT IN AVERAGE RETWEETING

Regression Analysis

- We performed generalised linear mixed model (GLMM) to identify which emotional variables (i.e., joy, confidence, anger, fear and sadness) explain the number of retweets generated by a message, whilst controlling for variables regarding both user perspective (i.e., the number of friends/followers that a given user has, the number of tweets that a given user has marked as favourite and the number of tweets issued by the user) and message perspective (i.e., the number of URLs, hashtags, emojis and @username contained in a given tweet).

TABLE 3. REGRESSION ANALYSES TESTING RETWEET AND EMOTIONALLY CHARGED TWEETS FOR DEMOCRATS VS. REPUBLICANS

	DEMOCRATS			REPUBLICANS		
	β (SE)	*CI*	*t*	*β (SE)*	*CI*	*t*
(Intercept)	-5.34 (.33)	[-5.98, -4.69]	-16.20***	-5.90 (.29)	[-6.46, -5.33]	-20.48***
Joy	**-0.71 (.08)**	**[-0.87, -0.54]**	**-8.59*****	**-0.23 (.04)**	**[-0.30, -0.16]**	**-6.28*****
Confidence	**-0.13 (.13)**	**[-0.38, 0.12]**	**1.03**	**0.03 (.06)**	**[-0.08, 0.14]**	**0.50**
Anger	**0.34 (.25)**	**[-0.14, 0.83]**	**1.36**	**0.27 (.09)**	**[0.10, 0.43]**	**3.16****
Fear	**0.56 (.19)**	**[0.19, 0.91]**	**-2.99****	**-0.01 (.17)**	**[-0.35, 0.32]**	**-0.08**
Sadness	**-0.27 (.11)**	**[-0.49, -0.05]**	**-2.42***	**0.18 (.06)**	**[0.05, 0.30]**	**2.85****
Status count	0.45 (.81)	[-1.14, 2.03]	0.55	1.40 (1.20)	[-0.93, 3.73]	1.18
Favourites count	-1.27 (.94)	[-3.12, 0.57]	-1.35	-0.92 (1.74)	[-4.34, 2.50]	-0.52
Friends count	1.02 (1.02)	[-0.98, 3.02]	0.99	-0.18 (1.01)	[-2.15, 1.79]	-0.18
Followers count	4.05 (.92)	[2.24, 5.85]	4.40***	3.56 (1.67)	[0.27, 6.84]	2.12*
URLs	-0.40 (.05)	[-0.50, -0.29]	-7.49***	-0.26 (.03)	[-0.32, -0.19]	-8.41***
@Usernames	-2.30 (.41)	[-3.10, -1.50]	-5.63***	-1.38 (.19)	[-1.74, -1.01]	-7.39***
Hashtags	-2.96 (.31)	[-3.56, -2.35]	-9.62***	-1.35 (.20)	[-1.74, -0.95]	-6.71***
Emoticons	-0.64 (.58)	[-1.77, 0.50]	-1.10	-1.66 (.59)	[-2.81, -0.51]	-2.83**

Note. *** $p \leq .001$; ** $p \leq .01$; * $p \leq .05$. 95% confidence intervals. Using min-max normalization to scale data. Missing values have been omitted in each model.

- By adjusting for other variables, both parties' followers were less inclined to act upon content that expresses joy (β = -.71, SE = .08, p < .001) in the Democratic camp, and (β = -.23, SE = .04, p < .001) in the Republican camp. Confidence had no impact on retweeting preference among either side of the political spectrum.
- However, dissimilarities were clearer when examining their responses to negative tweets. Whereas anger proved a key driver in the Republican camp (β = .27, SE = .09, p < .01), the results showed no significant response to such emotions in the Democrat camp.
- By contrast, there were quite different results for fear which, although having no impact on Republican followers, came out as the leading emotional factor inspiring retweets in Democrat followers. Specifically, fear based tweets predicted increases in the expected retweet count, a significant effect (β = .56, SE = .19, p < .01).
- Sadness yielded mixed results: for Republicans, sadness based tweets were more likely to be retweeted (β = .18, SE = .06, p < .01), while for Democrats, sadness predicted decreased retweets (β = -.27, SE = .11, p < .05).

CONCLUSION

- The current study used data from the 2018 US Midterm Election to compare emotional content of 76 politicians' tweets before testing what emotional content spread farther and faster online.
- Our data revealed that fear based tweets by Democratic candidates were most shared on social media, while anger based tweets by Republican candidates were most shared on Twitter.
- Politicians' tweets signalling sadness were more likely to be retweeted when they were from Republican candidates, but less likely to be retweeted when they were from Democratic candidates.
- Positive tweets signalling joy by both Democratic and Republican politicians were less likely to be shared on social media, while the degree of confidence expressed in the tweets were unrelated to diffusion on social media.

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