Information, Communication & Society

ISSN: 1369-118X (Print) 1468-4462 (Online) Journal homepage: https://www.tandfonline.com/loi/rics20

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INFORMATION, COMMUNICATION & SOCIETY
https://doi.org/10.1080/1369118X.2020.1748086

Positive sentiments as coping mechanisms and path to resilience: the case of Qatar blockade

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ABSTRACT

Existing research on coping accentuates the role of positive emotions as defensive mechanisms to cope with stressful situations and the ensuing negative emotions. The same literature justifies the long-term effects of positive emotions that help build lasting resilience. Grounded in theories of coping and resilience, this paper (1) identifies the emotions that people actuate to cope with adversaries and (2) evaluates the resulting long-lasting adaptation and resilience. To do this, we examined the emotions felt by Qatar residents due to a land, sea, and air blockade enforced by neighbouring counties. Accordingly, we analysed 160,000 Arabic tweets originating from Qatar between June-2017 and March-2018 using a novel machine-learning algorithm termed *Weighted Conditional Probability*. Our algorithm achieved state-of-the-art performance when compared with the often-used Support Vector Machine, Naïve Bayes and Deep Neural Nets algorithms. Results show that, while Qatar residents experienced an emotional roller coaster during the blockade, they used positive emotions like love and optimism to cope with adversities and accompanying emotions of fear and anger. Moreover, our analysis reveals that their adaptive resilient capacities gradually strengthened during the nine months of blockade. The study supports the renowned theory of positive emotions using an advanced methodology and a large-scale dataset.

ARTICLE HISTORY
Received 29 November 2018
Accepted 18 March 2020

KEYWORDS
Resilience; coping; sentiment analysis; opinion mining; machine learning

Introduction

Research in social psychology has a long history of examining the effects of positive and negative emotions in different contexts. Negative emotions like anger, sadness, and fear are often experienced during stressful events such as terrorist attacks (Waugh, 2003), major changes related to the work environment (Khan et al, 2017), and health problems (Ferrer et al., 2017). On the other hand, positive emotions like love and optimism can help divert people's attention from the negative emotions and are often heightened to cope with

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stressful event (Folkman & Moskowitz, 2000; Folkman, 2008; Lazarus, 2000; Moskowitz, 2001). For example, people experience a heightened level of love when they face social difficulties such as the loss of a close friend or family member (Fredrickson, 1995). Actuating positive emotions as defense mechanisms are found to better cope with stressful situations and ensuing negative emotions (Cohn et al., 2009; Tugade & Fredrickson, 2004; Yendork & Somhlaba, 2017). Moreover, recent studies confirm that people that use positive emotions not only better cope with stressful situations they face but also develop long lasting resilience to better cope with future stressful events (see Armstrong et al., 2011; Cohn & Fredrickson, 2009; Gloria & Steinhardt, 2016; Khan et al, 2017).

In recent years, people have flocked to social network platforms like Facebook and Twitter to express their emotions and share them with their personal networks. Statista.-com which compiles statistical data on users of different social network applications recently revealed that the number of Facebook and Twitter users reached 2.2 billion and 275 million users respectively. While Facebook is still the most popular networking application, Twitter remains the main microblogging platform where users share over 200 billion[1] short messages – or tweets – per year with their followers. To this end, a large number of researchers choose this platform to analyae sentiments. Massive corpora from twitter is extensively used by economists, governments, academics, marketers, and more in order to identify sentiments on a broad range of subjects (El-Masri, Altrabsheh, and Mansour, 2017a). Some of the most recent examples of sentiment analysis research using twitter data include Cambria et al. (2017), Gaspar et al. (2016), Sharma et al. (2018) to name a few. Notwithstanding the convenience of having access to abundant amounts of data from Twitter, sentiment analysis research accentuates the difficulty in examining such short, abbreviated, erroneous, and messy textual data (Gaspar et al., 2016). Those problems are amplified when tweets are in Arabic; even more so when in non-standard form (Al-Ayyoub et al., 2018; El-Masri, Altrabsheh, & Mansour, 2017a; Mohammad, 2016; Nadeem, 2019). Indeed, while sentiments in the English language have been thoroughly researched in recent years little efforts have been exerted on Arabic sentiment analysis (El-Masri, Altrabsheh, Mansour, and Ramsay, 2017b). Finding accurate techniques to measure sentiments by mining Arabic tweets cannot be timelier especially given the current turbulences and social changes in the Middle East and more specifically in the Persian Gulf region.

On 5 June 2017, Saudi Arabia, United Arab Emirates, Egypt and Bahrain cut off their diplomatic relations with the state of Qatar claiming that its Emir's statements regarding Iran were incendiary. On that day, a sudden split between countries in the gulf countries emerged to become one of the major conflicts between nations who historically saw themselves as one family. Saudi Arabia, UAE, Egypt and Bahrain enforced a brutal air, sea, and land blockade on the little peninsula. The main demands of the blockading countries were that Qatar must reduce its diplomatic relationships with Iran, stops its military coordination with Turkey, and closes the Al-Jazeera media network. The Qatari government rejected these demands. On the other hand, the residents of Qatar expressed heightened sentiments on social media, specifically due to the uniquely close ties with the involved gulf countries. Qatar citizens who live in the blockading countries were forced to leave. Moreover, UAE, Bahraini, and Saudi citizens who live in Qatar were asked by their governments to return to their homelands as well. These demands led to separating family members who have disparate UAE, Bahraini, Saudi, and Qatari nationalities. Anger, pessimism, sadness, disgust, and other negative feelings dominated the daily discussions on and off the social networks. At the same time a positive sense prompted by nationalism kept the Qatari people strong and united driven by love and optimism among other sentiments.

Accordingly, in this paper, the authors investigate the sentiments of the residents of Qatar After the blockade. The primary goals of this work are threefold. First, we show how sentiments in Qatar evolved during the first 9 months of this tragedy. The sentiments examined are sadness, anger, fear, disgust, pessimism, love, joy, anticipation, trust, surprise, and optimism. Second, we exhibit the intense changes in sentiments due to major events that transpired at different times during the 9 months period after the blockade. The last and perhaps most important goal is to examine the concept of resilience in the context of post-blockade Qatar and demonstrate how residents used positive ones like love and optimism thereby reinforcing their resilience to better cope with negative sentiments like fear and anger resulting from stressful events. To conduct this kind of sentiment evaluation, the authors advance an artificial intelligence programmes they termed Weighted Conditional Probability and juxtaposed it against some of the leading machine learning algorithms including Support Vector Machine (SVM), Naïve Bayes (NB), and Deep Neural Networks (DNN). The programmes came second worldwide in SemEval (2018) which is a yearly sentiment analysis competition run at the International Workshop on Semantic Evaluation.

The paper is structured as follows. First, we review the relevant literature on sentiments, coping, and resilience. Afterwards, we describe the research methodology and the analysis performed and discuss the results. We conclude by identifying the implications and limitations as well as specifying avenues for future research.

Literature review

Coping with adversities

Humans tend to balance their negative emotions with positive ones in order to improve their well-being (Diener et al., 1991). A well-known research stream in positive psychology finds that humans not only nurture positive emotions in themselves but also in people around them improving their psychological and physical health (Fredrickson, 2004, Fredrickson & Joiner, 2018; Choi et al., 2019). Those positive emotions become 'efficient antidotes for the lingering effects of negative emotions' (Fredrickson, 2004). Abundant research, mostly through human experiments, empirically supports these claims (see Aspinwall, 2001; David et al., 2014; Garland et al., 2010; Reed & Aspinwall, 1998 Trope & Neter, 1994;). For instance, a study of US college students' emotions after the terrorist attack of September 11 showed a 60% increase of love towards their families and friends to cope with feelings of anger, fear, and sadness (Saad, 2001).

Perhaps more importantly, those positive emotions, accumulated overtime become resources that outlive the ephemeral adversarial emotional state to fuel psychological resilience (Stein et al., 1997). The interplay between positive emotions, coping with adversities, and durable resilience is evident in a positive psychology research. This reciprocal causality is empirically supported in extant research (see Cohler, 1987; Folkman & Moskowitz, 2000; Masten, 1994).

In positive psychology research, a well-established theory that articulates such research is the broaden-and-build theory by Fredrickson (2004). Two key hypotheses of this theory are (1) the 'undo hypothesis' – stipulating that positive emotions might 'correct' or 'undo' the aftereffects of negative emotions – and (2) the 'bounce back hypothesis' – arguing that positive emotions, overtime, fuel psychological resiliency.

Resilience

The American Psychological Association (2014) defines resilience as 'the process of adapting well in the face of adversity, trauma, tragedy, threats or even significant sources of stress'. The concept definition of resilience is consistent across different fields of study such as medicine (Norris et al., 2009), sociology (May, 2018), psychology (Karam et al., 2014; Luthar et al., 2000), ecology (Barthel, 2016), and mental health (Charbonneau, 2019). In this paper, and in line with prominent psychology literature, we refer to resilience as the positive adaptation within the context of significant adversity (Luthar et al., 2000).

In psychology, resilience has been studied in different contexts; most notably during stressful events that individuals and societies experience like terrorism, health problems, depression, disorders, and work problems (Butler et al., 2007; Luthar et al., 2000; Seligman, 2011; Southwick & Charney, 2012). On the individual level, this concept is often referred to as psychological resilience and is considered a personality trait that echoes the proficiency of humans in adjusting to unstable environments (Cohn et al., 2009). Humans can develop resilience when exposed to major threats or hardships if they are able to adapt to new unfavourable situations (Rutter, 1990). In such environments, positive emotions have been found to result in elevated future resilience levels (Cohn et al., 2009). In other words, resilience is considered a human capability that facilitates recovering from negative events by utilising emotions that are positive, like love and optimism, in order to cope (Tugade & Fredrickson, 2004).

On the societal level, resilience is referred to as social or community resilience. It denotes the 'capacity of social groups and communities to recover from, or respond positively to, crises' (Maguire & Hagan, 2007). Some relevant research on social resilience looks at the ability of societies to work together and respond to adversities like natural disasters (Burton, 2014; Keim & Noji, 2011; Maguire & Hagan, 2007; Reuter & Spielhofer, 2017) and terrorism (Fredrickson et al., 2003). More recently, Keck and Sakdapolrak (2013), defined social resilience as comprised of (1) Coping capacities (the ability to cope with adversities), (2) Adaptive capacities (the ability to learn from past experiences and adapt to future defies), and (3) Transformative capacities (the ability to develop foundations that nurture individual and societal sturdiness to face future adversities).

Coping capacities are reactive and short-lived, whereas adaptive and transformative capacities are proactive and trigger long-term changes in a society's ability to handle adversities (Keck & Sakdapolrak, 2013). This view is consistent with the seminal works of Galatzer-Levy et al. (2018), Bonanno et al. (2015), and Southwick et al. (2014) who view resilience as a temporal trajectory characterised by a relatively short-lived period of disequilibrium and a long-term period of positive adjustment and adaptation. Pertaining to emotional capacities, such capacities can be observed on social media. How people of a particular society emotionally deal with adversities on social media can be considered a measure of their social resilience. That said, resilience as the result of online social interaction via the use of positive emotions has not been adequately examined. Some research that recently touched on this phenomenon using social media data, albeit lightly, includes the seminal work of Gaspar et al. (2016) who showed how tweeters cope with threatening events using sentiment expressions like optimism, trust, and hope.

Sentiments on social media

The co-occurrence of negative emotions resulting from stressful and adverse events followed by positive emotions to cope with those events have been recently examined in recent years using social media data. For instance, Panagiotopoulos et al. (2014) examined the negative emotions of English citizens on twitter resulting from riots and how that triggered positive emotions and closer collaborations between the government bodies and the people. Another example of such findings on social media is in a recent examination of a food contamination incident in Germany by Gaspar et al. (2016) in which the authors demonstrated how optimism and hope were key emotions to cope with anger and disgust.

The analysis of text on social media is considered specifically suitable when unforeseen stressful events transpire (Gaspar et al., 2016). Text shared on social media has been used to examine people's negative sentiments towards adverse political events, football results, and TV shows to name a few (Ott, 2017; Thelwall et al., 2011). Sentiment analysis denotes the automatic valuation of feelings from text (Mohammad, 2015). There have been different attempts to define a concise set of emotions. Ekman (1992) suggests six basic emotions which are happiness, anger, disgust, fear, sadness, and surprise. Those emotions are still being used, e.g., in Chen et al. (2017) and Poria et al. (2013). Plutchik (2001) developed a new concept he labelled the Wheel of Emotions (1980) that contained eight bipolar emotions which are joy versus sadness; anger versus fear; trust versus disgust; and surprise versus anticipation. More recently, sentiment analysis, specifically conducted on social media data expanded those lists to include a set of 11 positive and negative emotions which are anger, anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise, and trust. Those emotions have been extensively use in international competitions such as SemEval (https://competitions.codalab.org), with recent research aimed at multi-label emotion classification, where a single tweet may be assigned zero, one or more than one of a set of labels, to analyse sentiments on twitter of different languages like English, French, Spanish, and Arabic (e.g., Cortis et al., 2017; De Bruyne et al., 2018; Nakov et al., 2016).

Research methodology

The primary objective of this research is to examine the sentiments of the Qatari society; i.e., residents of Qatar, during the first 9 months of the blockade. Specifically, we seek a deeper understanding of (1) the main sentiments experienced by Qatari residents during this period, (2) the coping mechanisms (or lack thereof) they employed to deal with the events related to the inflicted blockade, and (3) their ability to build long-term resilience to help them cope with adversities. Our examination of sentiments is grounded in the broaden-and-build theory of positive emotions put forward by Fredrickson (2004). Specifically, we validate two key hypotheses of this theory:

(1) The ‘undo hypothesis’ – in the short-term positive emotions can ‘undo’ the effects of negative emotions, and
(2) The ‘bounce back hypothesis’ – in the long-term positive emotions fuel psychological resilience allowing adaptation to future adversaries and maintaining psychological and physical well-being (Fredrickson, 2004; Keck & Sakdapolrak, 2013).

The dataset used is a large corpus of tweets that were extract from twitter via the twitter API (Application Programming Interface) and stored in a mongoDB database on a data-mining server. To ensure that the tweets originated from Qatar, we specified in the Twitter API request the longitude and latitude of the centre of Qatar along with the point radius that covers the whole peninsula. Moreover, we only collected the Arabic tweets that contain the word قطر (Qatar). Around 450 thousand tweets were collected. After removing the duplicates and retweets, we ended up using 160 thousand tweets for data analysis.

In order to provide support for the aforementioned theory of positive emotions, we used a novel machine learning system (described by Ahmad et al., 2018a, 2018b) to analyse a collection of tweets obtained over the relevant period.

This system involved a number of key stages, as follow:

- Preprocessing: Arabic tweets tend to contain large amounts of noise, such as non-Arabic words, various kinds of Romanised transcriptions, emojis and emoticons and other hard-to-handle items. We cleaned up some of the material, removed non-Arabic items (the tweets contained Persian, Chinese and other characters which seemed likely to be irrelevant to the task at hand), and developed systematic ways of identifying and handling emojis and emoticons. We also used the tagger and stemmer described by Albogamy and Ramsay (2016a, 2016b) to obtain canonical forms for lexical items. Stemming (i.e.,; reducing a word to its root form) tweets, where the vocabulary is very open-ended, and the standard rules of word formation are not followed very systematically. That said, the tagger and stemmer described by Ramsay and Albogamy have been shown to be better than any competing systems for tweets and using them produced a significant improvement in the performance of the tool.
- Classification: we developed a classifier which made use of a weighted combination of the conditional probabilities that a tweet expressed a given sentiment given that it contained a given word. The algorithm was developed for carrying out multi-label classification, where a single tweet may express zero or more sentiments from a predefined set. This is a more difficult task than simply classifying a tweet as belonging to one class or another. The algorithm we used, which is described in detail in (Ahmad, 2019; Ahmad et al., 2018a; 2018b), gives extra weight to words that are important for specific emotions, and also allows a word to give a negative score for a sentiment. The results are substantially better than can be obtained by using the well-known naïve Bayes classifier. Testing on a range of datasets suggests that this algorithm outperforms state vector machines and deep-neural networks when only a limited amount of training data is available (Ahmad, 2019). Indeed, several of the entrants in the Semeval 2018 competition that performed less well than our algorithm used these approaches.
- Cleaning: we trained the algorithm on a subset of the training data, and then ran it on a disjoint development set. At this point it turned out that some words that had a positive score for some sentiment actually occurred in more tweets that did not express that

sentiment than ones that did, and vice versa. We therefore reset the scores for these words to be 0 for the sentiment where this happened.

- Threshold setting: some of the sentiments that we were looking for are very clean and obvious markers; others did not. It therefore made sense to set different thresholds for the various sentiments, which we did by running the model on the development set and finding the optimal threshold for each sentiment.

We entered this system in the SemEval 2018 sentiment classification competition. The organisers of this competition supplied training and development sets of tweets, where each tweet was manually assigned 0 or more sentiments from a predefined set of 11 sentiments (i.e., it was a multi-label classification task, where it is not known how many, if any, of the labels should be assigned to each tweet). Entries were allowed to use other externally supplied data such as word-embedding models and other annotated data, but we simply used the 2.5 K tweets that were supplied by the organisers. This algorithm came a very close second in the Arabic section of the competition[2] and is extremely fast, and hence was convenient for analysing the 160,000 tweets in our collection. The version of the tool that we used for the work reported in the current paper was trained on the SemEval Arabic data.

Data analysis

In order to achieve the aforementioned objectives; we collected around 160,000 Arabic tweets that originated from Qatar between June 2017 and March 2018. Consistent with the training dataset of SemEval (2018), our analysis pertained to the eleven sentiments defined for the competition. Those sentiments are sadness, anger, fear, disgust, pessimism, love, joy, anticipation, trust, surprise, and optimism. The results revealed that the residents of Qatar experienced an emotional roller coaster during the first nine months of blockade.

Plotting the daily averages for the various sentiments allowed us to look at specific events and at trends. Both of these turned out to be significant when trying to interpret people's reactions to the blockade, which had local spikes corresponding to specific events as well as longer-term trends as people came to terms with what was happening. The clear correspondence between major events and spikes in the plots was intrinsically interesting but was also reassuring – while the competition results showed that the tool performed well when tested on data that was similar to that on which it was trained. There was no guarantee that it would also work on data collected under different conditions. In the absence of large-scale annotation of the 160,000 tweets we cannot calculate statistics such as the various kinds of F-measure, but the fact that we have a clear correlation between major events and the emotions found by the algorithm suggests that its findings were rooted in reality.

Qualitative validation of the sentiments expressed in Qatar during the blockade

To validate the results, we looked for spikes in positive sentiments and we mapped them to the most relevant news on Qatar of that day. In order to identify the most relevant news, we looked at google news (news.google.com) and used google sorting feature to identify the most important blockade event of the day based on news relevance. We also used Aljazeera's dedicated page on events related to the blockade to identify the main events of the day. Our results showed that the spikes in sentiments that our algorithm identified from the collected tweets corresponded to significant blockade-related events, simultaneously confirming that the results obtained by controlled testing in the SemEval experiments transfer effectively to real world scenarios and allowing us to probe the way that people reacted to these events. In order to ensure that the sentiments that Qatari residents exhibited during these periods were indeed related to the blockade, we extracted a random subset of 10% of the sentimental tweets of the events' dates and the two following days and asked two university students to label them as either blockade-related or not. The result of this qualitative analysis revealed that the majority (approximately 89%) of the analysed tweets were related to the blockade. We also evaluated the consistency of the labelling that was conducted by the two students using the inter-observer agreement Kappa measure (see Landis & Koch, 1977). The Kappa value was 0.96 indicating a high level of labelling consistency as per Landis and Koch (1977).

As shown in Figure 1, the main event (17 August 2017) from the news outlooks was that Saudi Arabia will allow Qatari pilgrims to perform Hajj. Qatar welcomed the news. Accordingly, our data showed a spike in optimism (from 7% of tweets showing optimistic sentiments to 22%) and a decline in pessimism (from 5% to 2%).

Another example of a radical change in sentiments (3 July) relates to the change of position of the US government in relation to Qatar. More specifically, president Trump reviewed his earlier position suggesting that Qatar supports terrorism and said that Qatar is a partner in fighting terrorism and encouraged GCC unity. Harmoniously, the sentiments associated with joy spiked from 7% to 20% while sadness declined from 4% to 2% (see Figure 2). A similar radical change occurred on July 9 when the chief prosecutor of the International Criminal Court praised Qatar and regretted the actions of the four blockading countries. Simultaneously joyful tweets increased to 14% and sad tweets declined to 2% (see Figure 2).

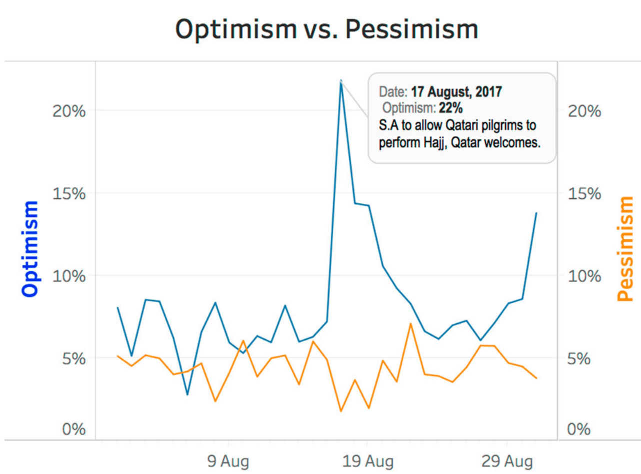

Figure 1. Change of Sentiments due to S.A. allowing pilgrims to perform Hajj.

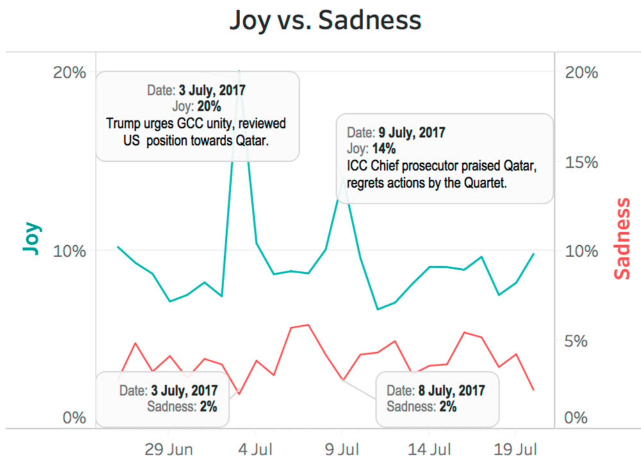

Figure 2. Change of Sentiments due to Trump's Review of Position.

These spikes show that analysis of sentiment in tweets can provide reliable and almost instantaneous information about public reaction to major political events.

The undo hypothesis: coping capacities of Qatari residents

The second question that we sought answers for is how the residents of Qatar were able to cope with stressful events and adversities. To do this, we identified the two most fearful events during the 9 months period of the blockade that witnessed the highest ratio of tweets with sentiments of fear. Those days were:

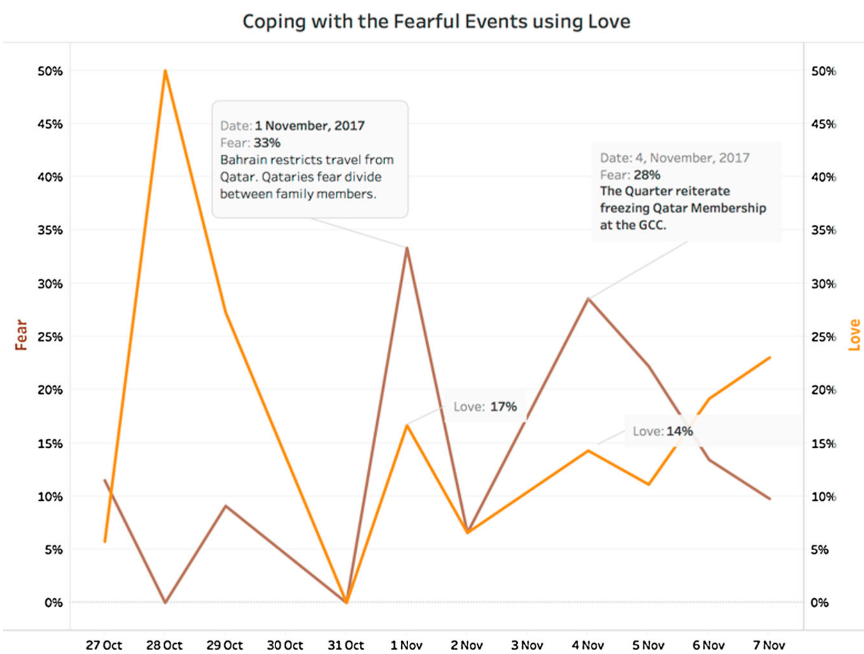

Figure 3. Coping with the most fearful sentiments observed on Twitter with Love.

1 November 2017: This day was observed to be the most fearful day for the residents of Qatar when 33% of tweets exhibited fearful sentiments (see Figure 3). It was when Bahrain imposed entry visas on Qatar nationals and residents which divided many families that had members in both counties.

4 November 2017: This day was observed to be the third most fearful day for the residents of Qatar when 28% of tweets exhibited fearful sentiments (see Figure 3). It was when the foreign ministers of Saudi Arabia, Bahrain, UAE, and Egypt met in Abu Dhabi and reiterated freezing the membership of Qatar at the Gulf Cooperation Council.

As shown in Figure 3, Qatari residents expressed love sentiments simultaneously with fear sentiments in order to cope with stressful events such as the ones described above. Indeed, to cope with the events of 1 November and 4, Qatari residents tweets expressing love sentiments shot up to 17% and 14% from 0% and 7% respectively.

In addition to the spikes in love tweets expressing love sentiments that signifies their strategies for coping with these fearful events, Qatari residents also expressed joy at the same time they expressed the most fear from the two main fearful events. Specifically, on 1 November and 4, joy sentiments on twitter went up to 17% and 29% from 0%, and 6% respectively (see Figure 4).

The results described above are in line with Fredrickson's Undo hypothesis and consistent with Keck and Sakdapolrak (2013) and Bonanno et al. (2015) who view coping capacity as short-lived and reactive. As evident in Figures 3 and 4, there are short-lived periods of disequilibrium in emotions (upward and downward spikes) in order to undo the negative sentiments that resulted from adverse situations.

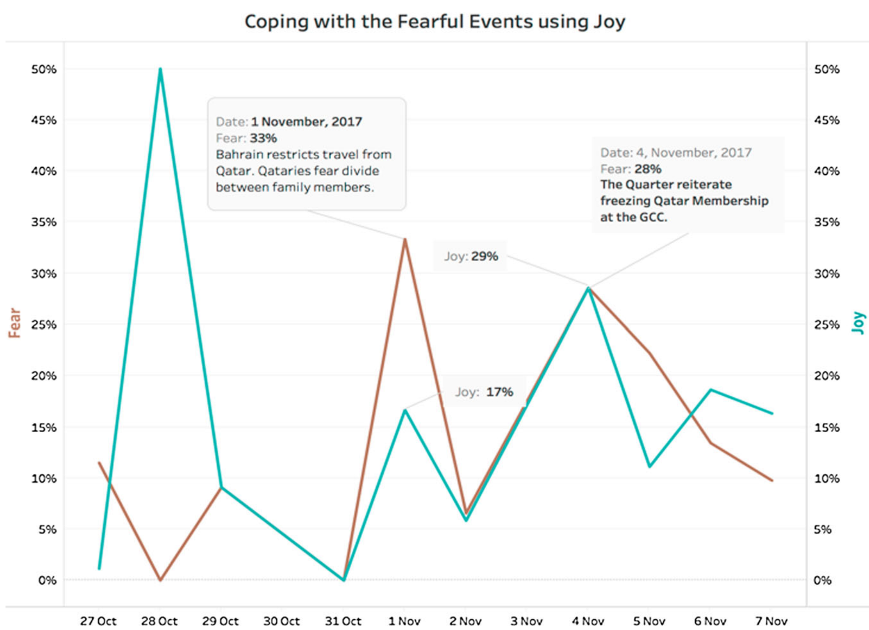

Figure 4. Coping with the most fearful sentiments observed on Twitter with Joy.

The bounce back hypothesis: adaptive capacities of Qatari residence

Our third and final analysis of the results is to validate the bounce back hypothesis – whether, in the long-term, positive emotions become resilient mechanisms maintaining psychological well-being. To examine the change in resilience of Qatari residents, we examined the changes of all eight sentiments over the period of 9 months. We expected that the ratio of negative sentiments would gradually decrease, and the ratio of positive sentiments would increase over time indicating longstanding adaptation to handling threatening situations. To this end, we plotted the eight sentiments overtime and looked at trend-lines. Figure 5 shows those trends.

As shown in Figure 5, the three positive sentiments, namely optimism, joy, and love continued to improve throughout the duration of the 9 months after the blockade. Optimism steadily increased from an average of 7% of the total number of tweets to 17%. Similarly, joy went up from 8% to 22%. Lastly, love slowly increased from 10% to 20%; albeit briefly descending to 9% early on in August 2017. Moreover, pessimist tweets gradually declined from 4% to 3% of the total number of tweets. Likewise, anger dropped from 28% to 13%, and disgust from 28% to 15%.

Discussion

The sentiment analysis algorithm that was developed and used to examine the emotional state of Qatari residents achieved a relatively high accuracy rate (macro F1 score = 0.475 and micro F1 score = 0.608). Our evaluation of the events (using news.google.com and aljazeera.com) that stirred those emotions provide further support for the accuracy of

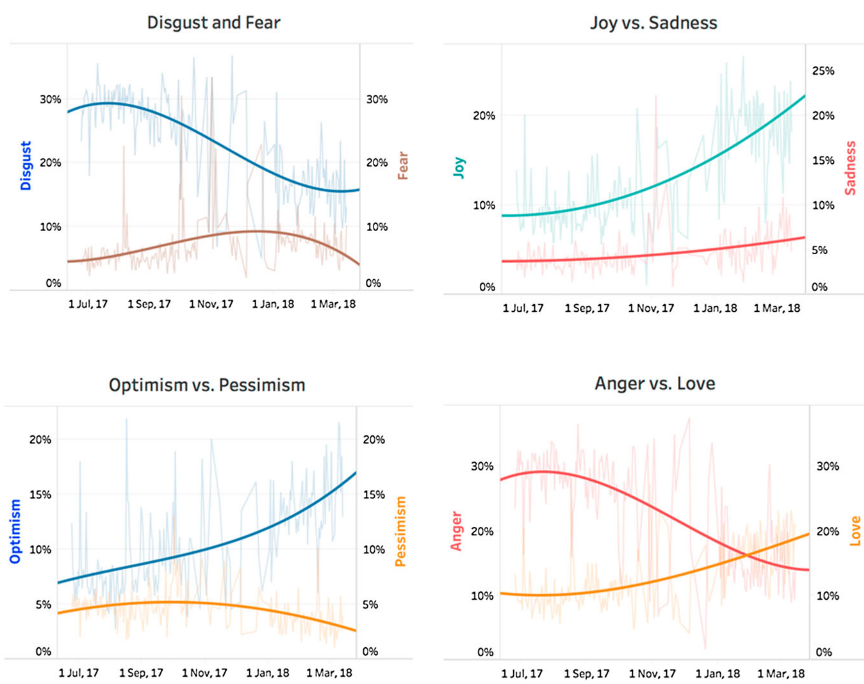

Figure 5. The Adaptive Capacity of Qatari Residence.

our algorithm. Indeed, the spikes shown in Figures 1 and 2 confirm that analysis of sentiment in tweets provided reliable and almost real-time information on public opinion about political events.

It is noteworthy to distinguish between the upward spikes in positive sentiments and those in negative sentiments. As Figures 3 and 4 show, when positive sentiments spike upwards, they are accompanied by downward spike of negative sentiments. Such changes are sentiments is rational as people feel less negative and more positive. When people are more optimistic and joyful, they are less pessimistic and sad. Such changes in sentiments are evident in our data. For instance, the first spike in Figure 3 shows that when love spiked upwards, fear declined and when joy spiked upward as portrayed in the first spike of Figure 4. Conversely, this phenomenon is reversed when there are spikes in negative sentiments. Indeed, consistent with Fredrickson (1998) theory of positive emotions and with the conceptualisation of resilience of Keck and Sakdapolrak (2013), positive sentiments spike upwards accompany negative sentiments to cope with stressful events as it is evident in Figures 2 and 3. We can only conclude that those upwards spikes in love and joy are reactive and short-lived defense mechanisms to cope with stressful events that trigger fear and anger.

On the other hand, adaptive capacities, as defined in Keck and Sakdapolrak (2013), correspond to the slow progress of a society's ability to learn from past experiences and adapt its sentimental reactions in future stressful events. This long-term adaptation allows a society to continuously improve its handling of adversities (Bonanno et al., 2015; Fredrickson, 2004; Keck & Sakdapolrak, 2013; Southwick et al., 2014). Consistent with the assertions and findings in the relevant literature, our findings reveal that building resilience transpires through the constant and gradual acclimatisation to stressful events using positive emotions. Indeed, while the radical expressions of love and joy (see Figures 3 and 4) were reactive coping mechanisms to deal with short-term in response to threats, slow and steady improvements of positive sentiment expressions (see Figure 5) indicate the development of resilient emotional foundation to content with future obstacles.

Obviously, negative sentiments are expected to weaken overtime which is shown in Figure 5 above. In fact, the ratio of tweets showing disgust shrunk from 28% to 16% and anger contracted to 15% from 28%. That said, pessimism shrunk only 1% to 2% and sadness went up 2% points to 6%. The average ratio of fearful emotions in March 2018 was the same as it was in June 2017. From the charts above, one can observe how negative sentiments such as disgust, anger, pessimism, and fear had curvilinear trends. This behaviour seems natural given that societies express negative emotions as consequences of events but then express positive ones to cope with those events. The average ratio of negative emotions such as disgust and anger peaked slightly at the beginning of the blockade (in July) signifying how Qatari residences really feel about the situation. In the short-term, they coped with extreme increases in positive emotions and eventually equipped themselves with lasting resilience to fight their negative emotions and stabilise them. Conversely, their feelings of fear continued to intensify for over six months until it was skilfully controlled. Over the entire period, sadness loomed on Qatari residents, though faintly, for all the period examined signifying that Qatari residents have not yet been able to control the sadness they experience due to the split between them and their neighbours.

Implications

From a theoretical perspective, this paper contributes to the existing literature of two research streams, in the fields of psychology and artificial intelligence. Pertaining to the former field and to the best of our knowledge, this effort is the first to validate Fredrickson's broaden-and-build theory of positive emotions using a novel machine-learning algorithm and analysing a large dataset (160,000 records) extracted from twitter. Predominantly, theories as such are supported using conventional methods such as questionnaires, interviews, or experiments. Accordingly, our investigation complements previous efforts by providing further support to a well-established theory by analysing a large longitudinal data that we extracted from social media over a period of 9 months. With respect to the field of computer science, more specifically, artificial intelligence, this effort highlights the importance of tailoring sentiment classification algorithms in accordance with the nature of text being analysed. While algorithms such as SVM, NB, and DNN have been the primary classifiers of choice for social media dataset, we found that our WCP algorithm achieved a higher accuracy scores.

Conclusion and future work

Coping and developing lasting resilience to adverse situations that trigger negative emotions have long been studied in the fields of psychology and sociology. Established theories such as the broaden-and-build theory (Fredrickson, 1998) have been examined on the individual and societal levels with consistent results. Extant literature emphasises and provides evidence of how individuals and societies cope with present adversities and build lasting resilience to handle future ones by using positive emotions. Americans used love to cope with sadness and anger after the September 11 attack. Certainly, over time Americans also built resilience to cope with adversities. One can contemplate the resilience of Americans to the endless gun shootings in schools and public places. Similar to Americans, Qataris who have long lived in peace and prosperity amongst their larger gulf family need to gain such resilience and the blockade, ironically, helped build it.

In this paper, we provide an alternative approach to examine the concepts of emotional coping and resilience. A large number of tweets were scrutinised over a longitudinal study to gain a better understanding of how emotions evolve and how the positive ones are utilised to undo negative emotions in the short-term and build resilience in the long-term. The machine-learning algorithm that we used to achieve higher accuracy scores was designed with the nature of the analysed data in mind. While the vast majority of machine-learning based sentiment analysis research focus on algorithms such as support vector machines and naïve Bayes, and more lately deep neural nets, our WCP (Weighted Conditional Probabilities) algorithm took into account the interactions between the analysed classes which were not easily captured with standard algorithms.

As other entrants to the SemEval 2018 Arabic sentiment analysis competition (e.g., Mohammad et al., 2018) found, 3 of the 11 sentiments were particularly difficult to capture, namely trust, anticipation, and surprise. Like most approaches to sentiment classification, our system depends on identifying key terms that signal particular sentiments, with the difference between systems lying mainly in the way that they make use of correlations between isolated words and sentiments. With moderate sized training sets, most bigrams only occur a small number of times – just 150 of the 33000 bigrams, i.e., less than 0.5%, in the SemEval data, for instance, occur more than three times. It is hence not possible to use bigram statistics, let alone N-grams for N larger than 2. If we look for pairs of words that occur in the same tweet, rather than restricting attention to adjacent words, we find that 4701 out of 280412 possible pairs, i.e., less than 2%, occur more than three times, which is again not enough to obtain any useful statistics from. We therefore need to find some more robust way of identifying tweets that express these emotions.

Applying a sentiment classification algorithm to longitudinal data, as described in this paper, can indicate trends in the way people view some events or situations, but it cannot say anything about why these trends occur. Linking spikes in some sentiment to note-worthy changes in the underlying situation can retrospectively suggest places where researchers might look in order to develop theories about such trends, but without an enormous amount of data it is not possible to apply machine learning techniques to discover or validate such theories automatically. It would be necessary to track hundreds, if not thousands, of major events over extended periods in order to find trends in the way that trends themselves develop, and the necessary data simply is not available. The machinery we have developed here can be used to inform the study of trends, and to confirm or disconfirm independently developed theories about the way that public opinion evolves in response to changes in the underlying situation, but it cannot replace more traditional approaches without an unfeasibly large amount of data.

Notwithstanding the implications of this research on theory validation, and more specifically the theory of positive emotions, this paper does not tap into the mechanisms by which negative sentiments that negative experiences trigger. Additionally, while we expect that the notion of nationalism and sense of community activate positive sentiments in societies, the scope of our investigation does not examine such phenomena. One avenue to further our research could be to examine how adverse events activate human sentiments as well as the reasons why concepts like unity and nationalism activate positive sentiments as coping mechanisms.

Acknowledgement

The publication of this article is funded by the Qatar National Library.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author, M.E. The data are not publicly available due to the enormity of the data. Specifically, we used data that we collected from Twitter over 9 months of tweets originated from Qatar which amounted to around 450,000 tweets out of which approximately 160,000 were original and 290,000 were either retweets.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This publication was made possible by the NPRP award [NPRP 7-1334-6-039 PR3] from the Qatar National Research Fund (a member of The Qatar Foundation). The statements made herein are solely the responsibility of the author[s].

Notes

1. www.internetlivestats.com/twitter-statistics/
2. Macro F1 score of 0.475 compared to the winner's score of 0.461, i.e. better than the winner on this score, micro F1 score of 0.608 compared to the winner's 0.618: micro F is often preferred because it provides a better reflection of a classifiers ability to deal with minority classes.

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