Sentiment of Armed Forces Social Media Accounts in the United Kingdom: An Initial Analysis of Twitter Content

Daniel Leightley, Marie-Louise Sharp, Victoria Williamson, Nicola T. Fear, and Rachael Gribble

Abstract Prior research on the United Kingdom (UK) public's perception towards the British Armed Forces often found a contradicting understanding of the military as both 'heroes' and 'victims'. In order to examine these contradictions further, this study examined public attitudes and perceptions of the British Armed Forces, using a sentiment analysis of Twitter content posted on or after 1 January 2014. Twitter is one of the largest social media platforms, with an estimated 126 million daily active users worldwide, and 17 million active users in the UK. A bespoke data collection platform was developed to identify and extract relevant tweets and replies. In total, 323,512 tweets and 17,234 replies were identified and analysed. We found that tweets related to or discussing the British Armed Forces were significantly more positive than negative, with public perceptions of the Armed Forces stable over time. We also observed that it was more likely for negative tweets to be posted late evening or early morning compared to other hours of the day. Furthermore, this study identified differences in how positive and negative tweets were discussed in relation to politicised hashtags concerning Government policy, political organisations, and mental health. This was an unexpected finding, and more research is required to understand the reasons as to why this is the case.

Keywords British Armed Forces · Social media · Mental health · Sentiment · Public perceptions · Public attitudes

D. Leightley (✉) · M.-L. Sharp · V. Williamson · N. T. Fear · R. Gribble
King's Centre for Military Health Research, King's College London, London, UK
e-mail: daniel.leightley@kcl.ac.uk

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1 Introduction

Public support for military action plays an important role in defence and foreign policy, from establishing the legitimacy of military operations to maintaining military effectiveness, justifying defence budgets, encouraging retention and recruitment, and ensuring support for veterans (Rahbek-Clemmensen et al. 2012; Gribble et al. 2015). Since the beginning of the UK's involvement in Iraq and Afghanistan nearly two decades ago, there has been widespread concern from military leaders about what the British public thought of these missions and how public perception might influence support for personnel and veterans on their return (Hines et al. 2015; Gribble et al. 2019). However, there has been, and continues to be, a lack of UK-based research on public attitudes towards the British Armed Forces from a UK perspective.

Evidence indicating differences in attitudes and perceptions between the general public and the armed forces is referred to as the 'civil-military gap'. First described in literature originating from the U.S., it refers to the cultural and demographic gap that can arise between society and members of the armed forces due to a lack of contact, shared experiences, and demographic representation (Huntington 1957; Biderman 1960). A widening gap can have implications for mutual understanding and support, defence and security policy, recruitment and retention of military personnel, and how well those leaving military service transition back into civilian society (Rahbek-Clemmensen et al. 2012). Prior research conducted in this area suggests a contradiction in the way in which the public perceive the British Armed Forces (McCartney 2011). A study using data from the British Social Attitudes survey, for instance, found high levels of public esteem and respect for the armed forces, with "more than eight out of ten people" saying they held "a 'high' or 'very high' opinion of the Armed Forces" (Gribble et al. 2012, 141). In fact, according to the study, service personnel were more respected than any other profession, including doctors, who regularly top the list of most respected professions (ibid., 143).

Differences in perceptions may stem from decreasing public contact with those who have served, or currently are serving, in the armed forces, following the shrinking of the military establishment after the Cold War and the passing of generations who experienced conscription for World Wars One and Two and the national service – which was abolished in 1963 in the UK (Strachan 2003). Furthermore, over the last 20 years there has been a marked shift in the role(s) and responsibilities of the British Armed Forces. Active combat missions in Iraq and Afghanistan have ceased and personnel are involved increasingly in non-combat operations, such as humanitarian responses, including Operation Gritrock in response to the Ebola epidemic in 2014, supporting first responders fighting the 2018 wild fires in England and Wales, and supporting residents in England during the widespread floods in 2019 and early 2020 (BBC 2018; Forces.Net 2019). However, despite such frontline, public-facing roles, research indicates that the general public do not understand the daily roles of the armed forces, given the reduction of the media focus on their current activities, which may contribute to more negative perceptions (Latter et al. 2018).

While there is a clear admiration for the British Armed Forces, this is often accompanied by misperceptions and misinformation about the impact of military service on those who served (Rahbek-Clemmensen et al. 2012; Gribble et al. 2015, 2019; Hines et al. 2015). British research shows that the public regularly overestimate the negative impacts of military service on military personnel and veterans, especially as regards mental health. The social research institute, Ipsos MORI, in collaboration with King's College London, conducted the 'Hearts and minds: Misperceptions and the military' study, an international survey on perceptions of the armed forces, for which a total of 5010 interviews were conducted across 5 countries: Australia, UK, USA, Canada, and France (Ipsos MORI 2015). The study found several misconceptions among the general population, which included overestimating the amount spent on armed forces, overestimating mental health problems, and overestimating former service personnel's impact on the justice system (ibid.). These findings are not unusual, with previous surveys showing that 91% of the British public believe it is to be expected that former service personnel have physical, emotional or mental health problems because of their service (Ashcroft 2012).

More recent online surveys indicate that such perceptions continue. For instance, a poll conducted by YouGov shows that UK veterans are perceived as inherently likely to be institutionalised, psychologically impaired or 'damaged' due to military service (Latter et al. 2018). Moreover, there is a general perception that veterans are less able to build relationships outside the armed forces. However, at the same time, the public also believe that military service develops positive attributes, such as self-discipline, loyalty, and self-reliance. Overall, these findings seem to reflect the aforementioned hero/victim dichotomy in the British public's understanding of the armed forces and their role (McCartney 2011). It also should be noted that such perceptions could have further implications regarding the public's support of military operations and thus the ability of the Government to enact foreign policy (Forster 2005; McCartney 2010).

In the UK, there is limited research exploring public perceptions of the British Armed Forces using traditional-based approaches, such as surveys or face-to-face interviews. The increasing costs of conducting large-scale quantitative surveys – and the difficulties recruiting enough participants – may prohibit future research in this area. There has been an increased reliance on online surveys, however, they remove the ability of contextualising responses and are often done remotely without any direct contact or relationship. An alternative methodology is the use of social media to monitor public opinion in response to current events in real time. Although concerns do exist for using social media, it is important to acknowledge that the use of social media can give a vocal platform to nameless individuals to promote their ideas and thoughts freely without balance, and that this could overshow and devalue other perceptions.

There is a growing use of Twitter to quantify public opinion and perception. For example, the sentiment computed from tweets and replies to tweets has been used to characterise public perceptions of eating disorders, vaccines, illness, and pain (Ashcroft 2014; Hines et al. 2015; Mahar et al. 2017). Twitter, a microblogging service provider, has an estimated 126 million daily active users, generating over 400 million tweets per day. In the UK alone, Twitter has over 17 million active users (Morgan 2001; Szayna et al. 2007). It is therefore an ideal platform for analysing public opinion of the British Armed Forces. In this study, we examined the applicability of sentiment and content analysis of Twitter, including tweets and replies posted both by members of the general public and on armed forces accounts, in order to understand public perceptions of the British Armed Forces. Thus, we intend to provide support for alternative methods of examining public perceptions in this area and to understand how social media can advance our understanding compared to prior literature.

2 Methodology

2.1 Study Design and Data Sources

This study was designed as a quantitative analysis of tweets and replies – including the use of hashtags – posted on Twitter by publicly available accounts relating to, or discussing the British Armed Forces. Three members of the study team[1] manually searched Twitter to identify relevant accounts. The inclusion criteria for the accounts were:

1. publicly accessible (non-private);
2. posts relating to or discussing the British Armed Forces (i.e., veterans' charity or an individual who served);
3. written in English;
4. posted on or after 1 January 2014[2];
5. have a minimum of 1000 followers at time of data extraction.

The researchers determined each account's suitability for inclusion based on the content of the tweets and replies posted by the account. Furthermore, we used the number of account followers to indicate trustworthiness and to ensure that we did not include any fake accounts ('bots') or new accounts that may lack trustworthiness.

The exclusion criteria for the accounts were:

1. no identifiable language;
2. only contained a link or image (indicative of spam tweets, also referred to as junk or spam tweets);

[1] Researchers: Dr Daniel Leightley, Dr Marie-Louise Sharp, and Dr Rachael Gribble.

[2] Prior to 1 January 2014, Twitter processed, collated, and disseminated Twitter content in a different manner, thus making a direct comparison pre and post this date unreliable.

3. a re-tweet with no comment;
4. contain 15 characters or less.

For data collection, we used the Twitter Streaming Application Programming Interface (API), which has rate-limits to ensure fair use, meaning that only 2500 tweets can be collected per account (Twitter 2019). For each Twitter account meeting the inclusion criteria, the API was used to extract the most recent 2500 tweets and, where possible, the replies to each tweet. The tweets were automatically collected and stored in a password-protected database. Data extraction was performed in May 2019 and included tweet/reply content, coordinates (latitude/longitude) of the tweet/reply, date of creation, predicted language of the tweet/reply, method of posting, and, if there was a reply, the user at whom the reply was directed.

Figure 1 shows a flowchart illustrating the process we followed for the analysis of the tweets and replies, along with the numbers of the included and excluded tweets and replies.

2.2 Data Cleaning

In order to analyse the extracted Twitter content, it was important to process the tweets and replies prior to the analysis and modelling to ensure that we did not model irrelevant or non-important features. This is a standard Natural Language Processing methodological procedure used in a number of studies (Jinwei Cao et al. n.d.; Gundlapalli et al. 2013; Leightley et al. 2019). For this purpose, the following text processing steps were applied to the tweets and replies to remove tweets and replies that were not of interest:

1. removing special characters that did not provide useful information, e.g., (&), (“, “), (∗), (+), (<), (>);
2. identifying replies and mentions to other users (represented by @) and removing hyperlinks;
3. removing the hashtag symbol (#) and divide any hashtags into multiple words with the objective of reducing the hashtag to core terms.

2.3 Sentiment Analysis

In classical content analysis, human readers qualitatively identify themes and concepts in the text, which is time-consuming and limited. In this study, in order to estimate the sentiments expressed in each tweet and reply, we used an automated, computer-based lexicon and a rule-based sentiment classifier called Valence Aware Dictionary for Sentiment Reasoning, or VADER for short (Gilbert and Hutto 2014). VADER, which classifies sentiment as well as the valence for each word to compute a positive, a negative, and a neutral score for each sentence, has been used in

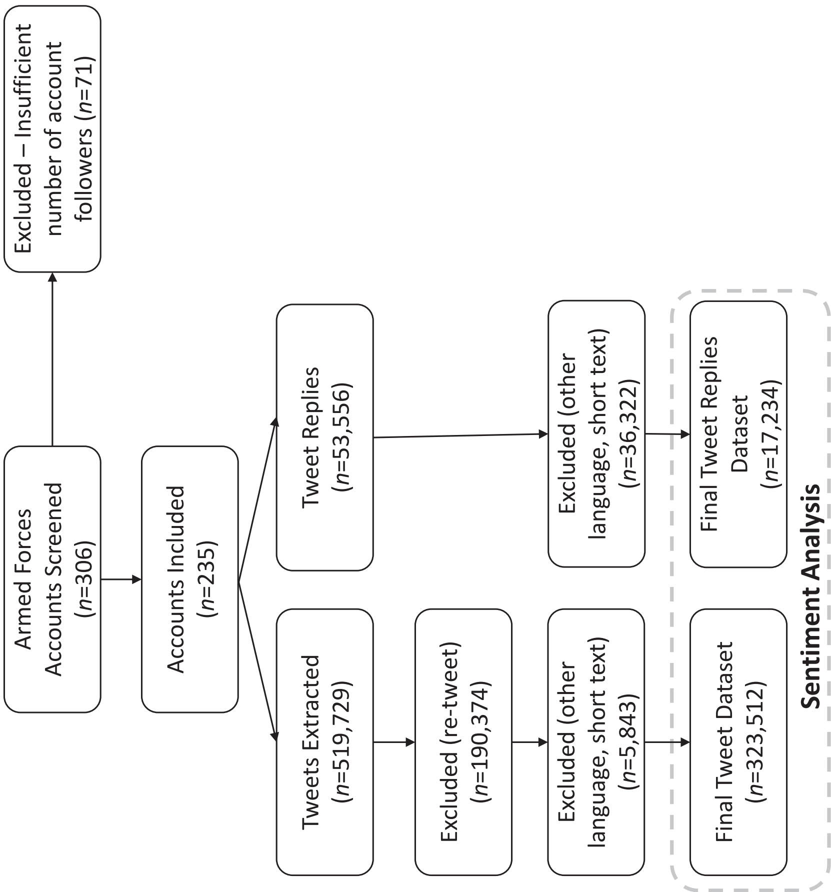

Fig. 1 Flowchart of data extraction and processing from retrieved tweets and replies

numerous studies to assess and predict sentiment (e.g., Daniulaityte et al. 2016; Ghani et al. 2018; Sewalk et al. 2018). VADER was selected as it was found to be successful in reliably handling social media text (Huang et al. 2018; Sewalk et al. 2018; Pérez-Pérez et al. 2019). We used VADER to compute the sentiment score for each sentence in the selected tweets and replies. As is practice in other approaches, we considered a sentence positive if the mean score was $\geq +0.3$, or negative if the score was ≤ -0.3. The mean of all nonzero scores was then used to calculate a sentiment score per tweet. Mean scores between -0.3 and $+0.3$ were considered neutral and were excluded from this analysis (Gilbert and Hutto 2014; Sewalk et al. 2018; Pérez-Pérez et al. 2019).

2.4 Additional Data Analysis

In this study, we leveraged our analysis to evaluate not only the expressed sentiment of each tweet and reply, but also the content and metadata provided with each tweet and reply. The literature indicates that time of posting, hashtags, and geolocation – where used or collected by Twitter – can offer unique insights that otherwise would not be captured by sentiment analysis alone (Kolliakou et al. 2016; Radzikowski et al. 2016; Roland et al. 2017). Specifically, the following features were extracted and analysed:

1. The day of the week and the time the content was posted were extracted for each tweet and reply. Previous research shows strong correlations between the sentiment score and the day of the week and the time the content was posted. For example, McIver et al. (2015) found that tweets posted early in the morning were often more negative compared to those posted in the evening, which may reflect psychological state changes throughout the day.
2. Twitter allows for the use of 'hashtags' in tweets and replies, which is included in the metadata. Hashtags (denoted with the # symbol) mark keywords or phrases and are categorised by Twitter. They summarise the overall narrative of a tweet/reply and reflect which topics the poster considers relevant and important (Radzikowski et al. 2016).
3. Some Twitter users have given permission for their location at the time of posting to be made publicly available. This could prove useful in identifying their current country of origin as well as distinguishing specific country issues, aiding in further decoding and understanding of the narrative of the tweet or reply, and validating any claims made (Radzikowski et al. 2016).

It is important to note that not all Twitter users will have used hashtags or have given permission for their location to be accessed and shared.

2.5 Statistical Analysis

The analysis conducted in this study largely follows analyses described previously, and uses the programming language Python (Kolliakou et al. 2016; Sewalk et al. 2018; Pérez-Pérez et al. 2019). Firstly, we provide unweighted descriptive statistics on the frequency, standard deviation (SD), and length of tweets and replies as well as average word length per tweet/reply, post rate per account, number of likes/retweets, average number of hashtags, and average number of tweets/replies posted in the morning or afternoon. Secondly, we sought to identify whether there were any differences between positive and negative sentiment scores, using a Mann-Whitney nonparametric test to determine whether sentiment statistically changed over time. Thirdly, we identified the most popular hashtags used for tweets and replies separately, based on a frequency count. The number of positive tweets for each hashtag was compared using Chi-square statistics, which was repeated for the replies. Finally, for those tweets and replies with a geolocation marker, we grouped and identified the most popular countries in which tweets/replies were made. Statistics were calculated using the whole denominator (*n*), unless stated otherwise (see Fig. 1).

3 Results

3.1 Descriptives

In total, 323,512 tweets and 17,234 replies were identified and extracted for analysis (Fig. 1; Table 1). The average number of characters was 115 for the tweets (SD: 41), and 59 for the replies (SD: 38). On average, each tweet was re-tweeted 3 times (SD:

Table 1 Top-level statistics for extracted tweets and replies

Statistic	Tweet (n = 323,512) mean (SD)	Replies (n = 17,234) mean (SD)
Character length	115 (41)	59 (38)
Tweet rate (per account)	10 (42)	5 (61)
Likes	3.09 (2)	0.47 (0.08)
Retweets	3 (8)	1 (2)
Hashtags	2.43 (3.07)	1.61 (0.21)
Images	0 (0.53)	0 (0.02)
Hyperlinks	0 (0.87)	0 (0.0)
Recipients (@)	1.2 (0.61)	1.24 (0.16)
Time period posted		
Morning (00:00–11:59 am)	8.34 (3.17)	2.46 (1.62)
Afternoon (12:00–11:59 pm)	16.07 (5.17)	2.01 (1.59)

SD standard deviation

8), and replies were re-tweeted on average once (SD: 2). Posters included an average of 2.43 hashtags (SD: 3.07) for tweets, and 1.61 hashtags (SD: 0.21) for replies. This study also identified that most of the tweets were posted after mid-day, i.e., between 12:00 and 11:59 pm (16.07, SD: 5.17), while most replies were sent before mid-day, i.e., between 00:00 and 11:59 am (2.46, SD: 1.62).

Using metadata for each tweet or reply, we were able to identify that the most popular methods to post a tweet or reply were Twitter for iPhone (28.55%, 21.31%), the Twitter Web Client (21.56%, 18.94%), and Twitter for Android (6.30%, 11.76%).

3.2 Sentiment Analysis

A higher proportion of tweets (48.70%; 157,576/323,512) was identified as having a positive sentiment score than a negative score (10.83%; 35,053/323,512). The reverse was found for replies, with 52.01 % identified as having a negative score (8963/17,234), and 38.78% (6683/17,234) identified as having a positive score. Quotations 1 and 2 illustrate the types of tweets and replies determined as being either positive or negative.

Figures 2 and 3 illustrate positive and neutral sentiment scores over time for tweets and replies, respectively. There was little variation in the deviation of sentiment scores over time, with no significant differences between positive and negative tweets or replies for each quarter included in the analyses. However, despite this, there was an overall downward trend in sentiment scores for tweets between Q1 2014 and Q2 2019, meaning that more negative tweets were being posted (−0.161). This was accompanied by an increase in the sentiment scores of the replies, meaning that more positive replies were being made (0.147). Although the decrease was not statistically significant, it could have been due to the higher number of tweets and replies and the rise in media attention the British Armed Forces received between 2018 and 2019, such as the investigation of former British Armed Forces personnel who served in Northern Ireland (Mills et al. 2019). Conversely, the increase in the sentiment scores of the replies during the same period could have been due to the response to negative media attention or negative Twitter content being posted. However, this increase again was not statistically significant.

Quotation 1: Example of a Positive Tweet and Reply

Tweet: “Serving in the #UK Armed Forces is the best decision I ever made and made me the man I am today #serving #military #proud”

Reply: “A big shoutout to the @ArmyLGBT team for joining @Lucianjay on air this week! It was great discussing life in the @BritishArmy and serving soldiers, who happen to be #LGBTQ. Happy Pride everyone”

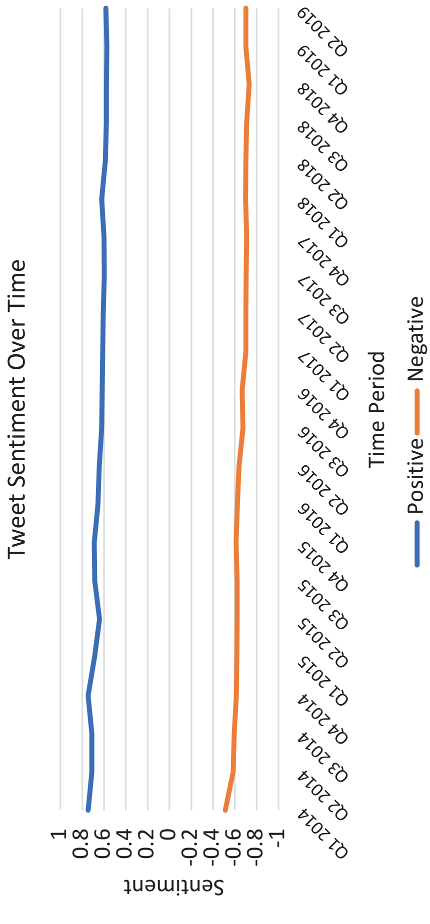

Fig. 2 Sentiment score for tweets from 1 January 2014 to 30 June 2019

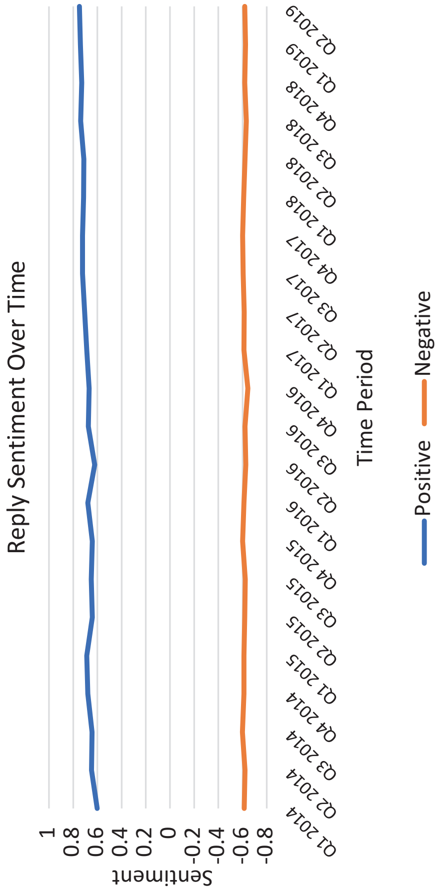

Fig. 3 Sentiment scores for replies from 1 January 2014 to 30 June 2019

Quotation 2: Example of a Negative Tweet and Reply
Tweet: "Countries would probably need less humanitarian aid if we didn't bomb them and sell weapons to countries that also bomb them #justsaying"

Reply: "@armyjobs The British government sells weapons to destabilise a foreign nation and then comes the British Army with this!"

In order to assess whether the time of day altered the sentiment score, we aggregated each tweet and reply into one minute blocks over a 24-h clock (Figs. 4 and 5). During the early hours of the day, both tweet and reply sentiment scores became more negative, whereas as the day progressed, sentiment scores improved (i.e., less negative, more positive content). Moreover, a significant difference between positive and negative tweets could be observed for the study's duration (p = 0.045), while significant differences were also found for tweet replies over the same time period (p = 0.022).

In order to further explore the role time plays for the positing of positive and negative tweets and replies, we also analysed the day of the week on which content was posted. Overall, we found no significant differences between the tweet and the reply sentiment scores (Figs. 6 and 7).

Figures 8 and 9 illustrate the sentiment score distribution of all negative and positives tweet, divided into histogram bins representing increments of *0.1* (sentiment score) to provide an overall representation of the sentiment score of all tweets and replies included in the analyses. Applying a Mann-Whitney nonparametric test revealed significant differences between all positive and negatives tweets (p = 0.041, $\mu = -0.04$, and SD, 0.709). This indicates that there is an overall difference between positive and negative tweets and replies. However, when stratified by time (i.e., Q1 2014), no differences exist.

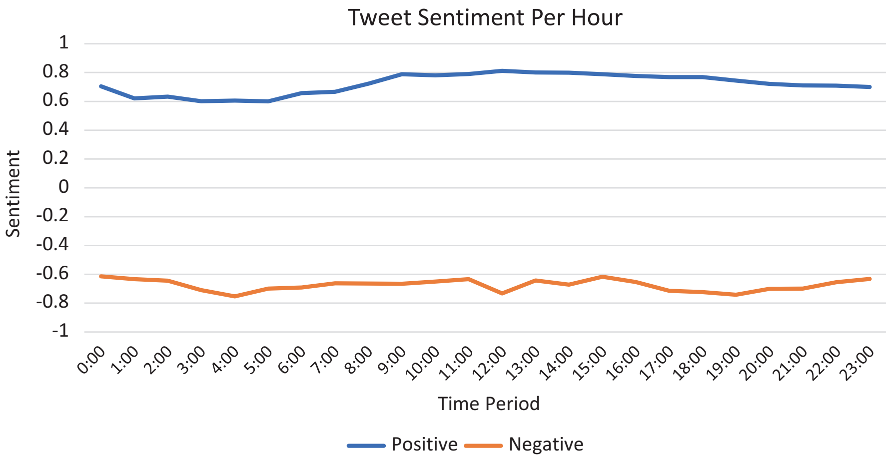

Fig. 4 Tweet sentiment score over 24 h of the day

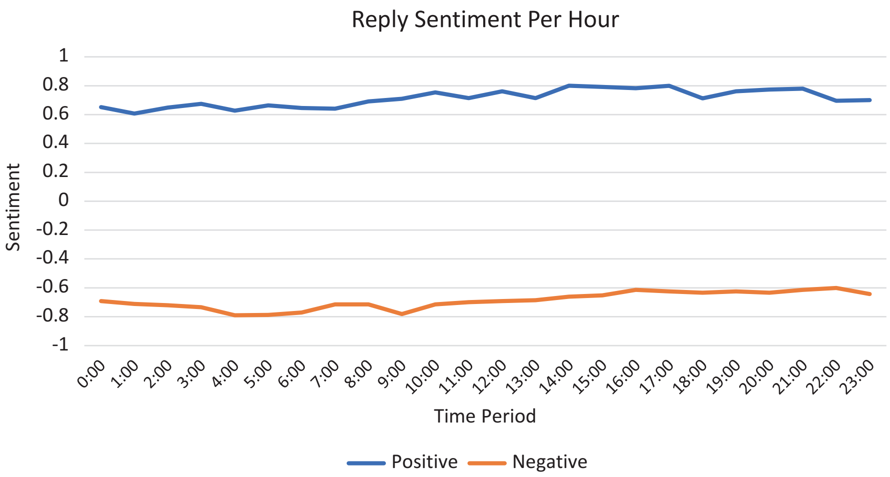

Fig. 5 Reply sentiment score over 24 h of the day

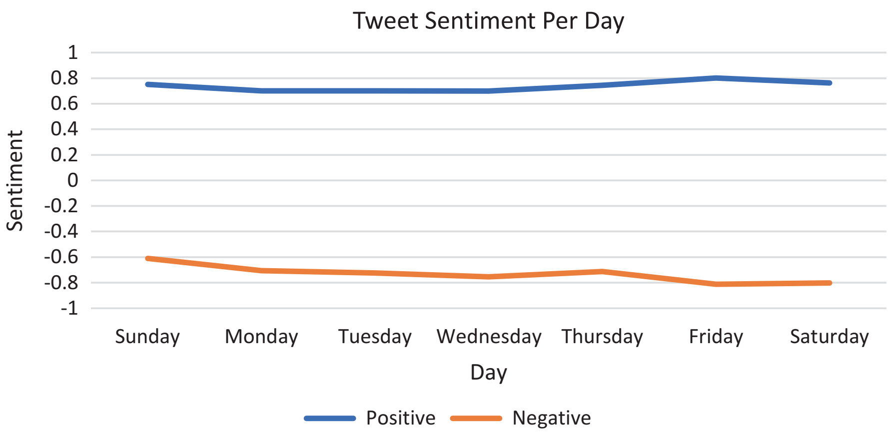

Fig. 6 Tweet sentiment score for each day of the week

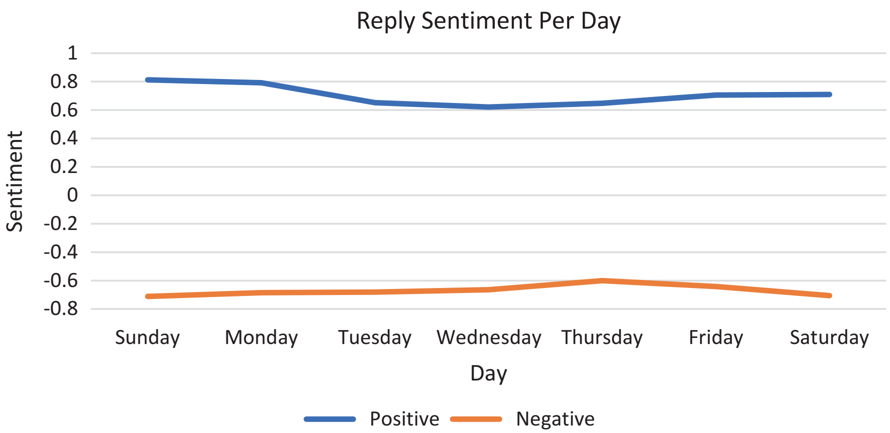

Fig. 7 Reply sentiment score for each day of the week

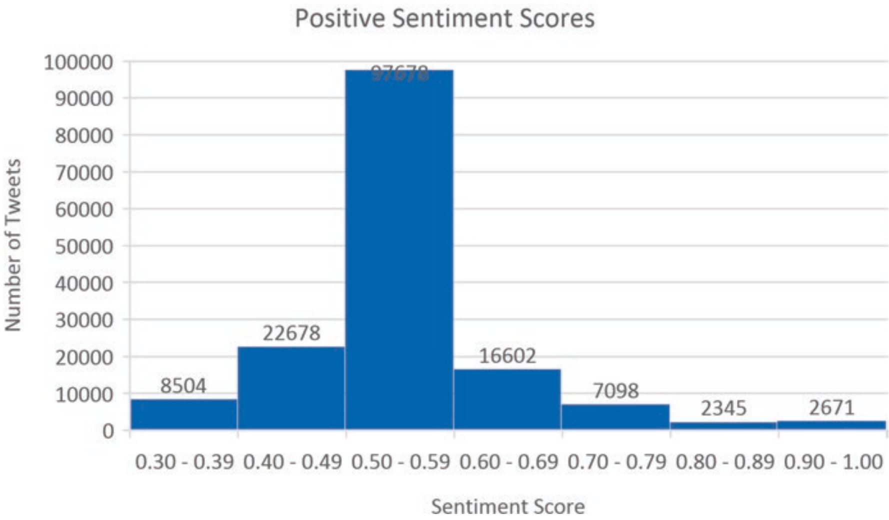

Fig. 8 Histogram spread for positive sentiment scores computed for tweets

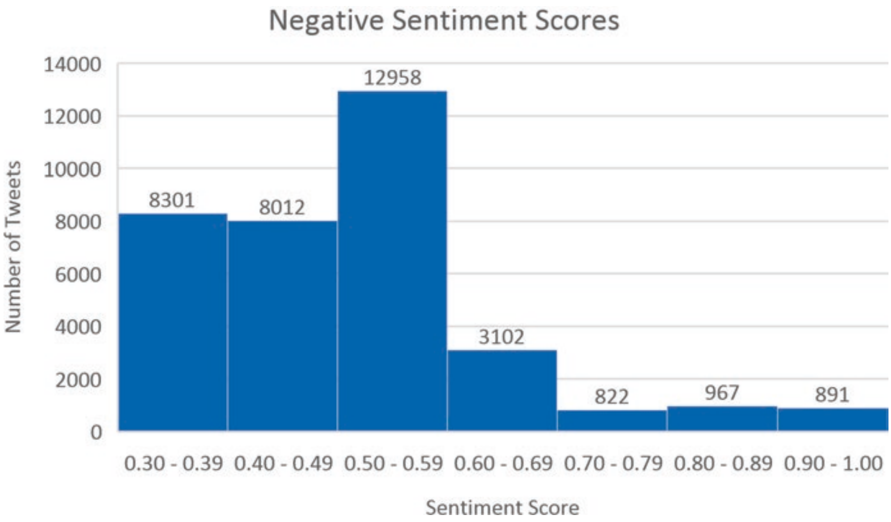

Fig. 9 Histogram spread for negative sentiment scores computed for replies

3.3 Hashtag Usage

A total of 111,014 (34.31%) tweets and 4128 replies (23.95%) included at least one hashtag (Table 2). The most popular hashtags used in the analysed tweets were '#mentalhealth' (8.27%), '#veteran' (8.14%), '#country' (3.87%), '#support' (1.24%), and '#NATO' (1.22%). The most popular hashtags in the replies were '#veteran' (12.46%), '#lestweforget' (8.68%), '#notinmyname' (5.45%), '#brexit' (4.99%), and '#labour' (2.71%). Statistically significant differences between positive and negative tweets were observed for the use of '#veteran' (44.00%, $p = 0.002$) and 'country' (49.94%, $p = 0.054$). Significant differences were also observed for tweet replies, for instance, for the hashtags '#veteran' (39.84%, $p = 0.001$), '#notinmyname' (12.97%, $p = 0.001$), and '#labour' (45.34%, $p = 0.002$).

Table 2 Top 5 hashtags computed by using the frequency of occurrence for tweets and replies

Tweet				Reply			
(n = 111,014)				(n=4128)			
Hashtag	n (%)	% positive	Chi^2 (p value)	Hashtag	n (%)	% positive	Chi^2 (p value)
#mentalhealth	9180 (8.27)	33.49	0.513 (0.473)	#veteran	514 (12.46)	39.84	14.486 (< 0.001)
#veteran	9036 (8.14)	44.00	14.466 (0.002)	#lestweforget	358 (8.68)	89.33	0.116 (0.733)
#country	4296 (3.87)	49.94	9.317 (0.054)	#notinmyname	225 (5.45)	12.97	31.158 (<0.001)
#support	1376 (1.24)	26.05	2.627 (0.267)	#brexit	205 (4.99)	48.10	9.317 (0.054)
#NATO	1354 (1.22)	58.30	2.576 (0.108)	#labour	111 (2.71)	45.34	21.278 (0.002)

3.4 Geolocation

In total, 75,766 tweets (23.41%) and 1047 replies (6.07%) had been assigned a geolocation marker, indicating latitude and longitude (Table 3). The most popular countries for posting a tweet were the UK (62.40 %), France (11.31%), Spain (7.34%), Portugal (7.19%), and Belgium (5.91%). The most popular countries for replying to a tweet were the UK (81.57%), Spain (4.10%), Belgium (3.61%), Falklands (3.44%), and USA (2.86%).

Table 3 Top 5 countries computed by using the frequency of occurrences where tweets and replies originated from according to Twitter's metadata

Tweet (n = 75,766)		Reply (n=1047)	
Country	n (%)	Country	n (%)
UK	47,277 (62.40)	UK	854 (81.57)
France	8569 (11.31)	Spain	42 (4.1)
Spain	5561 (7.34)	Belgium	37 (3.61)
Portugal	5447 (7.19)	Falklands	35 (3.44)
Belgium	4477 (5.91)	USA	29 (2.86)

4 Discussion

Overall, our findings indicate that public perceptions of the British Armed Forces were stable over time – between 2014 and 2019, no statistically significant changes were observed in the positive and negative tweets/replies analysed. These findings mirror those of the British Social Attitudes survey (Gribble et al. 2012) and illustrate that while the role of the British Armed Forces may be evolving post Iraq and Afghanistan, this appears to have little impact on perceptions, and the general public are still discussing the Armed Forces. This study did, however, find that although the day of the week a tweet or reply was posted was not significant, time of day was indeed a significant factor in determining the sentiment of a tweet or reply. Our study thus found that it was more likely for negative tweets and replies to be posted late in the evening or early morning compared to other hours of the day.

Previous research demonstrates the unpredictable and chaotic environment of social media, with a limitless variation in the content being posted at any time (Taecharungroj 2017). In this study, we found that a large proportion of tweets was identified as being positive, whereas more replies were negative. Generally, this occurred when individuals replied to a positive tweet negatively, which mimics observations made in the field of social media relations (Taecharungroj 2017). Over time this behaviour remained constant, even though the number of both positive and negative content posted increased. The unpredictable nature of Government policy and media portrayal also plays a significant role regarding the way in which the general public interact with social media. This may explain why differences were observed for the day/time of posting tweets and replies, given that news organisations are moving towards a 24-h reporting cycle and away from traditional reporting styles (i.e., reporting at 9 am).

The findings on the use of hashtags when discussing the British Armed Forces on social media provide new insight into the ways in which perceptions about the military may be politically motivated or informed through associations with current events, such as the 2016 EU referendum ('#brexit') and the 2019 UK parliamentary elections ('#labour'), and tied to particular cultural events like Remembrance Day ('#lestweforget'). This could be the result of blame, political attachment to wars, the rise of nationalism and racism due to Brexit or changes in UK Government policy regarding the armed forces (Ford and Goodwin 2017; Jennings and Stoker 2019).

Moreover, we found that the most popular hashtag associated was '#mentalhealth' for tweets, and '#veteran' for replies. We hypothesise that this may reflect the media attention on the mental health of British Armed Forces members, which resulted in an increase in public awareness regarding this issue (Ashcroft 2012; Lee 2016; Gribble et al. 2019). As UK research has shown, the public regularly overestimate the negative impacts of military service on military personnel and veterans, especially for mental health, which could explain why the majority of tweets using '#mentalhealth' were negative (Ipsos MORI 2015). Furthermore, the use of '#support' was often used in conjunction with '#mentalhealth' when tweeting. This could reinforce the notion that the public do not believe that the British Armed Forces are being supported enough as regards the mental health of their members.

A detailed analysis showed that there was a statistical difference in the use of '#mentalhealth' between positive and negative tweets, indicating a downward (more negative) focus. This could be due to users willing to be vocal on their thoughts and experiences relating to mental health and military service. Furthermore, media portrayals, such as the TV series 'Bodyguard' (Turner 2018), or veterans' stigma towards the access to and use of healthcare services could also influence public perceptions (Murphy and Busuttil 2015; Sharp et al. 2015). In this respect, it is important to acknowledge that the use of social media can give nameless individuals a vocal platform to promote their ideas and thoughts freely without balance, which could overshow and devalue other perceptions. In our analysis, we found that the most popular hashtags used were not impacted by a few 'vocal' accounts, but were dispersed, with the average number of the tweets and replies included in the study being around 9 per account.

Previous studies suggest that generally between one and two percent of tweets may contain geolocation metadata (Burton et al. 2012). However, in this study we found that approximately 24% of the tweets and 6% of the replies had a geolocation, which is significantly higher than was anticipated based on the literature. This may be due to bias, inaccurate recording or the proportion of tweets being posted by users who gave Twitter permission to collect this information. We found that the most popular country to post on the topic of the British Armed Forces was the UK. Nevertheless, interesting differences were identified between tweets and replies. While tweets were often made within countries where NATO activities were taking place, replies appear to have originated mostly from countries to which British nationals emigrate.

4.1 Strengths and Limitations

This study represents the first of its kind to explore the applicability of sentiment to Twitter analysis. As was the case in prior research (Gribble et al. 2012), this study found that public opinion is stable over time, with similar, albeit non-significant trends of positive and negative tweets and replies posted between 2014 and

2019. This study contributes to the academic literature by using robust and in-depth data analytics techniques to improve our understanding of public perceptions of the British Armed Forces. Furthermore, it introduces a new area of research on the politicisation of armed forces within public discourse. The method used in this study has been shown to be appropriate for this research area and could be applied in future work to provide real-time feedback on changes in recruitment strategy, mental health support, and government policy or future military operations.

The results of this study need to be considered in light of the following limitations. Firstly, this study included accounts that were manually identified. While this was systematic in nature, following the broad principles used for systematic reviews (Moher et al. 2009), future work should seek to develop more robust and automated solutions for account identification. Secondly, this study restricted the analyses to tweets and replies referring to the British Armed Forces. Thus, although the results indicated a stable trend over time, it is unknown whether this only reflects the trend of Twitter discussions on the armed forces alone. In order to address this concern, future work should extend the analysis to comparisons with other countries and occupations. Thirdly, we did not seek to separate or identify differences between active and veteran service members. Future work should therefore explore the role the active service status plays for public sentiment. Furthermore, the changes should be quantified to assess the impact positive and negative political changes, such as the EU Referendum, have on public perceptions. Finally, this study captured only a small proportion of Twitter content posted since 2014. It was limited in the number of tweets that could be collected due to Twitter API, and captured only the perceptions posted on Twitter. Moreover, the analyses were not weighted to consider the number of tweets per user account. Thus, future work should focus on the development of a longitudinal cohort of social media, specifically curated to focus on content and topics related to the British Armed Forces.

5 Conclusions

This study found that tweets related to or discussing the British Armed Forces are more positive than negative. In contrast, replies to tweets were found to be more negative than positive. For both tweets and replies, the sentiment remained stable over time, with little variation in the proportionality. In addition to sentiment scores, this study analysed the frequency of hashtags, observing variations in the use of politicised hashtags relating to Government policy or political organisations. It is not known why these differences occurred. Overall, the results of the analyses conducted for this study demonstrate that further work is required to understand the context and content of tweets and replies quantitatively and qualitatively.

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