The affiliative use of emoji and hashtags in the Black Lives Matter movement: A Twitter case study

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Protests and counter-protests seek to draw and direct attention and concern with confronting images and slogans (1–3). In recent years, as protests and counter-protests have partially migrated to the digital space, such images and slogans have also gone online (4–6). Two main ways in which these images and slogans are translated to the online space is through the use of emoji and hashtags. Despite sustained academic interest in online protests (7–9), hashtag activism (10–12) and the use of emoji across social media platforms (13–15), little is known about the specific functional role that emoji and hashtags play in online social movements. In an effort to fill this gap, the current paper studies both hashtags and emoji in the context of the Twitter discourse around the Black Lives Matter movement.

Introduction

Protests and counter-protests have long made effective use of images and slogans (1–3). As protests and counter-protests have partially migrated to the digital space, such images and slogans have also gone online (4–6). Two important ways in which these images and slogans appear is through the use of emoji and hashtags.

Some emoji have readily identifiable offline counterparts—such as the raised fist, which was first deployed as a standalone image in protests in the San Francisco Bay Area and Harvard University in 1968-9 (1), and which now has its own emoji. Similarly, some hashtags (like #BlackLivesMatter) reflect well-known offline slogans. Indeed, on Twitter since 2016, this hashtag is automatically enhanced with a small emoji-like sticker featuring a trio of raised black, brown, and white fists. The use of other emoji and hashtags, however, can be more obscure. To shed some light on their functions, we here study emoji and hashtags embedded in tweets associated with the Black Lives Matter protests in 2020, including the right-wing backlash to those protests. We analyze a dataset covering both the lead-up to and the aftermath of the 25 May 2020 murder of George Floyd by Officer Derek Chauvin in Minneapolis.

The nine-minute video of Floyd's murder set off a firestorm of backlash to those protests. We analyze a dataset covering both the lead-up to and the aftermath of the 25 May 2020 murder of George Floyd by Officer Derek Chauvin in Minneapolis. The nine-minute video of Floyd’s murder set off a firestorm of activity both in the streets and online (see also SI Appendix).

While the use of hashtags as an organizing mechanism in online activism has been studied (10), the role of emoji in social movements has, to the best of our knowledge, received no academic attention. At the same time, as emoji have become an increasingly popular form of communication, a growing body of work that tracks the various types and uses of emoji has emerged (13–15). Extrapolating from this literature, we present and test four hypotheses regarding the use of emoji in online activism. First, emoji might be used for their straightforwardly semantic content, functioning as compact logograms that efficiently convey meaning within the tight character constraints of Twitter (H1). Second, emoji and hashtags might be employed to disambiguate tone in the context of highly-charged discursive exchanges (H2). This follows from the observation that emoji and hashtags enable us to track important linguistic subtleties—such as sarcasm and humour—that are otherwise hard to detect in computer-mediated communication (16–18). Third, emoji might operate on par with extensive interlocutory gestures that aim at drawing and directing attention to the content of a given message (16, 19–21) (H3). Finally, emoji and hashtags might function as primarily affiliative gestures, drawing attention to the author of the tweet and demonstrating their bona fides within...
their group (H4). This fourth function is especially relevant with respect to the use of skin-tone modifiers, which have been associated with enhanced self- and group-identification (22). Given that hashtags can be understood as organizing mechanisms that connect people with shared interests (10) and systematically codify their shared interests under a common descriptor (23), people who employ the same hashtags may also do so to signal that they are members of the same community.

In addition to testing these four hypotheses (H1-H4), we are also interested in the broader question of whether there are discernible and meaningful differences in the ways that the various groups of participants involved in the Black Lives Matter discourse use emoji and hashtags. Accordingly, we employ social network analyses, classification algorithms, natural language processing techniques, conditional probability modelling, and regression models to answer the following two questions:

- **RQ1.** Are there informative and meaningful differences in the way that the various communities involved in the Black Lives Matter discourse employ emoji and hashtags?
- **RQ2.** Assuming there are differences, what is their functional significance?

Our work suggests that communities use emoji and hashtags in distinctive and meaningful ways. Further, it shows that emoji and hashtags are something of a mixed bag: they tend to decrease engagement with tweets, but increase engagement with the other tweets of authors who use them. This suggests that emoji and hashtags might play a primarily affiliative role in the communities we studied.

**Methods**

**Materials and Methods**

In this section, we explain the methods used to collect, clean, and curate our dataset.

**Data collection and cleaning.** We queried the Twitter Streaming API with a series of Black Lives Matter (BLM)-related keywords, hashtags, and short expressions in a window between January and July 2020. We used a sliding window to take into account that between 80%-90% of retweets occur within 5-7 days, with diminishing returns beyond (24). The dataset comprised ∼4.6M original tweets between January 13th and July 18th and ∼94.5M retweets from January 18th to July 23rd; these tweets were produced by ∼2.0M distinct authors. After the murder of George Floyd (May 25th 2020), the number of daily tweets increased by several orders of magnitude (from ∼255k to ∼4.35M).

**Social Network Construction.** We generated a retweet network (25), a weighted directed network where nodes are authors and the weight of an edge from node u to node v represents the number of times that user v retweeted user u. Self-retweeting was disregarded. Given this definition, users who retweeted but who did not author any tweets could not be nodes in the network. Having built the retweet network, we took the largest connected component (∼689k nodes, ∼13M edges) for further analysis. (See SI Appendix for technical details).

**Community Clustering and retweet statistics.** To find clusters, we used igraph (26) and the Python leidenalg package which implements the Leiden community detection algorithm (27). We found first-level clusters using Modularity Vertex Partitioning, preserving clusters with more than 10% of the original nodes. This gave 4 clusters, covering 83% of the graph. Next, we manually inspected the 100 most-influential nodes within each group. Based on this, we characterize the four communities as follows.

- **Activists:** this cluster represents the core of the movement and reflects the grass-roots nature of Black Lives Matter. It features a heterogeneous collection of individual activists, many of whom explicitly endorse the movement by placing #BlackLivesMatter in their profile bio.
- **Reactionaries:** this cluster features conservative politicians and public figures (e.g., Donald Trump, James Woods), as well as right-leaning media outlets (e.g., Breitbart News, The Gateway Pundit), anti-BLM activists, supporters of the police, and a large number of conspiratorially-minded and openly racist individuals. Additionally, this community features an exceptionally large number of suspended accounts. Though we cannot interpret these accounts, it stands to reason that they violated Twitter’s community guidelines regarding false (conspiratorial) and offensive (xenophobic) content.
- **Boosters:** this cluster comprises a diverse collection of individuals whose primary involvement with the Black Lives Matter movement seems to consist of link-sharing and fundraising. With respect to fundraising, we identify a large contingent of fans of the Korean pop phenomenon, commonly called K-pop. While the link between K-pop and Black Lives Matter might seem tenuous at first, the fact that one such band—Bangtan Sonyeondan (BTS)—donated a million dollars to the Black Lives Matter foundation, and encouraged its followers to match that donation, explains this group’s engagement (28).
- **Progressives:** this cluster contains a range of high-profile individuals and organizations that are generally supportive of the Black Lives Matter movement. In addition to prominent Democratic politicians (e.g., Kamala Harris, Bernie Sanders) and liberal media outlets (e.g., ABC, NBC, CBS), there are various non-profit organizations and legal aid foundations (e.g., ACLU).

**Classifier Construction.** The prospect of using emoji to train classifiers has received considerable attention and produced impressive results (13, 29). Classifiers are able to disambiguate the tone and intention of a given statement by differentiating between positive and negative valences of the same emoji (30-32). Extending this line of research, we investigated RQ1 by constructing a classifier of our own, with the goal of using emoji and hashtags for community detection. The goal was to provide a measurement of the linguistic cogency of the communities we identified through modularity analysis, and to provide a measure of entropy that shows how much additional information about community membership is contained within each type of communication.

We constructed a standard data-science workflow in Python for automated text classification, using Tensorflow for neural network approaches and Scikit-Learn (34) for classical classification techniques. Excluding members of the Boosters cluster because there were too few of them for meaningful analysis, we generated a document containing the plain text of all tweets by each user in the network, together with the emoji and hashtags they used. Tweet text was preprocessed using a typical text processing workflow (removing non-alphanumeric, non-hash identifier (#), and non-emoji characters, standardizing case, etc.), and emoji were encoded using Python’s emoji package (35). Further details on the data sampling, train/test splits, as well as evaluation, are available in the SI Appendix.

**Distinctiveness.** To examine the distinctiveness of each of the communities, we first determined the 15 most popular emoji for each community c and then for each emoji e. From that set we calculated Pr(ε|e). This gives a rough measure of how much information emoji and hashtag use carries about community membership, as well as which specific emoji and hashtags are most distinctive within each community.

**Emoji and Hashtag Co-occurrence Network Construction.** Though informative in its own right, we noted that a single tweet may well contain multiple emoji, multiple hashtags, and various combinations thereof. On this score, previous research has found that multiple hashtags are often combined to draw attention to interrelated issues.
RESULTS

Community Structure. As Figure 1 shows, the retweet network is bipolar, with Activists, Progressives, and Boosters on one side and Reactionaries on the other. This outcome is consistent with numerous findings from political science suggesting substantial polarisation in the political landscape (39, 40).

As Figure 2 shows, the murder of George Floyd triggered an outpouring of tweets—first among Activists, then among Progressives and Boosters, and finally among Reactionaries. The decay in the volume of tweets among these groups is also worth considering, as Reactionaries decay much less quickly than the other three communities, suggesting a self-sustaining dynamic within that community.

A. Classification Task. The results for the classification task are shown in Table 1 and warrant the following observations.

To begin, all classifiers with all data types greatly outperformed random classification, which for this task had an expected accuracy of ∼0.3333. Even the worst-performing classifier—Linear Stochastic Gradient Descent trained on emoji—obtained an accuracy greater than 0.5. More generally, we note that deep learning techniques marginally outperformed traditional approaches. More specifically, we find that the best-performing classifiers were GRU and LSTM neural architectures which take ordering into account, suggesting that the order in which emoji are presented in a given tweet makes a difference, perhaps because they occur in decreasing order of priority for the user.

With respect to RQ1, these results confirm that the various communities involved in the Black Lives Matter discourse use emoji and hashtags in distinctive ways. What is more, emergent patterns of emoji and hashtag use correspond with patterns of retweet behaviour (Figure 1), indicating that retweet engagement is associated with the use of emoji and hashtags. In addition to this, we find that hashtags are a particularly powerful marker of community membership and that, taken together, emoji and hashtags are roughly as informative as text in this regard.

Table 1. Classification task results

| Data Type | Log. Reg. | Rand. For. | Linear SGD | DNN | RNN | LSTM |
|-----------|-----------|------------|------------|-----|-----|------|
| emoji (E) | 0.62      | 0.61       | 0.56       | 0.58 | 0.64 | 0.64 |
| hashtags (H) | 0.72 | 0.70 | 0.70 | 0.71 | 0.73 | 0.73 |
| E + H     | 0.72      | 0.70       | 0.70       | 0.71 | 0.73 | 0.73 |
| text      | 0.74      | 0.69       | 0.73       | 0.72 | 0.74 | 0.73 |
| all data  | 0.76      | 0.73       | 0.76       | 0.76 | 0.77 | 0.76 |

Distinctiveness. Figure 3 shows the conditional probability of group membership given both emoji (3a) and hashtag (3b) usage. For each community, there are both emoji and hashtags that are extremely diagnostic of cluster membership. For example, the probability of belonging to the Reactionary group conditional on using a US Flag emoji is 87%. Angry ‘pouting’ and contemptuous ‘rolling eyes’ emoji are likewise significantly more likely to be used by members of the Reactionary cluster. Moreover, many of the hashtags used by Reactionaries are virtually pathognomonic, particularly those associated with the QAnon conspiracy theory. Though the distinction between Progressives and Activists is less sharp, there are discernible differences.

Fig. 1. Community rendering. Green: Activists, Blue: Progressives, Red: Reactionaries, Purple: Boosters. Forceatlas2 used for layout.

Fig. 2. Daily word-count sums of tweets associated with different communities. The vertical line indicates 25 May 2020, the day on which George Floyd was murdered. Date range: 17 January 2020 to July 23 2020.
Activists (Figure 4a) were strongly associated with the use of raised-fist emoji (ştir), hearts of different colors, and warning signals such as exclamation points (!). However, they tended to use lighter skin-tones and the default cartoon-yellow skin-tone more than their Activist counterparts. In addition, Progressives used the down-pointing finger (ään) more than Activists, suggesting that they were seeking less to demand recognition for themselves and more to redirect attention and concern for the demands of recognition being made by their Activist allies. Progressives also used emoji associated with electoral politics, especially the blue heart (❤️) and the blue wave (ימים), both of which are associated with support for Democratic political candidates (41).

In contrast to both Activists and Progressives, Reactionaries (Figure 4c) did not appear to center their attention on any single topic. Instead, different elements of this group pushed back against the Black Lives Matter movement in different ways. For instance, we see a large contingent drawing attention to the police via both emoji (blue heart ❤️, police officer 🇺🇸, police cruiser 🚔) and hashtags (e.g., #backtheblue, #bluelivesmatter), while other tweets seem to focus more on electoral politics, either by identifying with the Trump reelection campaign (e.g., #kag2020, #trump2020) or by derogating enemies (e.g., #democratsaredestroyingamerica, #liberalismisamentaldisorder). In addition, we see the centrality of the QAnon conspiracy theory to this community in its use of hashtags such as #qanon, #wwg1wga ("where we go one, we go all," a popular slogan in the QAnon movement), and #thegreatawakening. The Reactionary community does not seem to unite around a single cause or message; instead, they are primarily defined in terms of what they oppose. It appears that this reactionary movement in part reflects an attempt to hijack the Black Lives Matter discourse in order to bootstrap its own political agenda (42).
Fig. 4. Co-occurrence network of the emoji and hashtags used by each cluster. Node size = degree. Text and edge color = modularity class.
### Table 2. Descriptive statistics for emoji and hashtag use

| Community  | %E | %H | E-PR | H-PR | E-PR | H-PR |
|------------|----|----|------|------|------|------|
| Overall    | 26 | 57 | 3.69 | 1.92 | 2.86 | 1.72 |
| Activists  | 26 | 53 | 3.75 | 2.18 | 2.97 | 1.70 |
| Progressives | 26 | 67 | 4.25 | 1.96 | 2.52 | 1.22 |
| Reactionaries | 25 | 51 | 3.06 | 1.48 | 2.65 | 1.42 |
| Boosters   | 25 | 90 | 3.76 | 2.11 | 2.86 | 1.72 |

% E and % H give percentage of users in each group who use emoji and hashtags, respectively. E-PR and ~E-PR are mean pagerank of emoji and non-emoji users, each \( \times 10^{-6} \), H-PR and ~H-PR give the same for hashtags.

### Table 3. Retweet statistics for emoji and non-emoji users

| Community  | E-w/ | E-w/o | ~E | Type |
|------------|------|-------|----|------|
| Overall    | 34.96 | 47.57 | 37.12 | I   |
| Activists  | 55.51 | 105.79 | 74.69 | I   |
| Progressives | 22.24 | 30.74 | 17.6 | II  |
| Reactionaries | 27.07 | 26.52 | 25.29 | III |
| Boosters   | 61.86 | 44.71 | 46.77 | III |

E-w and E-w/o: mean retweets of tweets by emoji-users with and without emoji, respectively. ~E stands for mean retweets for users who never use emoji. See main text for definition of type.

### Table 4. Mean retweets for hashtag and non-hashtag users

| Community  | H-w/ | H-w/o | ~H | Type |
|------------|------|-------|----|------|
| Overall    | 31.58 | 51.21 | 40.07 | I   |
| Activists  | 63.19 | 96.33 | 91.92 | I   |
| Progressives | 19.1 | 32.04 | 18.44 | II  |
| Reactionaries | 24.65 | 34.81 | 16.22 | II  |
| Boosters   | 39.45 | 79.65 | 68.73 | I   |

Labels as per Table 3

### Usage Statistics

Descriptive statistics of emoji/hashtag (EH) use are given in Table 2. Across communities, about 25% of users have at least one emoji in one of their tweets. Hashtag usage is much higher, averaging about 57% but ranging as high as 90% in the Booster group. For all communities, both emoji- and hashtag-users have a higher PageRank, suggesting they are more embedded in the network as a whole.

Retweet statistics show several curious patterns for both emoji (Table 3) and hashtag (Table 4) usage. For ease of interpretation, we divide these into three patterns:

**Type I** patterns: when both the following conditions are met:
- EH-tweets by EH-users have fewer retweets than either non-EH tweets by EH users or by non-EH users (e.g., Activists who sometimes use emoji have their emoji-using tweets retweeted on average 55.39 times, compared to 74.76 times for non-emoji using Activists);
- where EH-users’ non-EH tweets are more frequently retweeted than either (e.g., the non-emoji tweets by Activists who used emoji in other tweets are retweeted far more than either; by 105.6 times).

**Type II** patterns: like Type I, save that EH-tweets by EH-users are roughly equivalent or have a slight advantage over non-EH users’ tweets.

**Type III** patterns: anything not in Types I and II.

Note that, with two exceptions, both the overall and community-level patterns fall into either Type I or Type II. That is, in general, EH-usage does not provide a substantial advantage in mean retweets, and often gives a substantial disadvantage, compared to tweets by people who never use them. However, EH-users’ other tweets are retweeted on average much more than non EH-users.

The two Type-III exceptions are found in Reactionaries’ use of emoji (which appears to make no particular difference to retweets) and Boosters’ use of emoji (which overall confers substantial advantages and may reflect the multilingual nature of this community and the fact that emoji can serve as a sort of lingua franca).

### Discussion

With respect to RQ1, Table 1, Figure 3, and Figure 4 provide compelling evidence that there are informative and meaningful differences in the way that the various communities involved in the Black Lives Matter discourse employ emoji and hashtags. The results of our classification task confirm that there are substantial advantages and may reflect the multilingual nature of the Black Lives Matter discourse. Furthermore, we find that hashtags are as informative as textual tweets in inferring communities, while emojis are almost as informative. This is significant for two reasons.

First, in terms of informational entropy, emoji and hashtags are more compact than text. Hence, they provide a computationally-efficient way of determining community membership. This is useful when dealing with large data-sets like the one analyzed here. Additionally, and in contrast to text, emoji and hashtags are freestanding expressions that can be interpreted even before considering syntactic complexities like word order or sentence structure. Based on nothing more than conditional probability analyses (Figure 3) and a co-occurrence matrix of emoji and hashtags (Figure 4), we were able to learn a great deal about the various communities involved in the Black Lives Matter discourse.

In addition to capturing the most obvious slogans (e.g., #BlackLivesMatter) and counter-slogans (e.g., #AllLives-
As for Activists’ focus on the attention-grabbing raised-fist, Progres-
sives and Boosters use the point-finger much more frequently.

Next, consider the use of interlocutory gestures and skin-
tone modifiers. With respect to interlocutory gestures, we
note the differential usage of ‘raised-fist’ (plers) and ‘pointing-finger’ emoji (plers). Compared to
Activists’ focus on the attention-grabbing raised-fist, Progress-
esives and Boosters use the point-finger much more frequently.

On the assumption that pointing-fingers direct rather than
draw attention, we infer that one of the contributions of Progres-
sives and Boosters to the Black Lives Matter movement
online is redirecting attention to Activists. Interestingly, these
same interlocutory emoji reveal a great deal with respect to
skin-tone modification. The fact that the Activist cluster
uses darker modifiers than the other communities lends sup-
port to Robertson et. al’s (22) observation that skin-tone
modifiers enhance self- and group-identification. At the same
time, we note the conspicuous use of non-modified, yellow,
‘default’ emoji within the Reactionary cluster. In light of this,
community’s racist attitudes, it is worth considering why its
members rarely employ the skin-tone modification function
to signal their whiteness. Here, we flag the possibility that
non-modified, yellow emoji might be a manifestation of the
ideology of colorblindness. In much the same way that the ide-
ology of colorblindness masks racism by rejecting it (47, 48),
non-modified emoji may maintain a pretense of neutrality
by ignoring any alternative. Furthermore, it may be that
widespread usage of this ‘default’ setting among white people
implicitly equates whiteness with normality.

In terms of RQ2, we started by proposing four hypotheses
about the functional roles of emoji and hashtags. In light
of our results, we come to the following conclusions. First,
H1 proposed that emoji and hashtags are principally used
for their semantic properties. There is some evidence for this,
e.g., Progressives’ use of the blue wave (blue flag) to predict and
courage the ‘Blue Wave’ election of Democratic politicians.
As for H2, which proposed that emoji are used to disambiguate
tone, our results suggest that this is not widespread. Indeed,
if this were the case, we would expect to see more emoji
such as sarcasm (sarcastic) and disdain (disdain) to modify the tone of a
retweet. Looking at Figure 4, this expectation is not borne out.
H3 posited that emoji might operate on par with ostensive
interlocutory gestures that draw and direct attention. While
this hypothesis holds to a certain extent in each of the four
communities, the prevalence of Type I and II patterns (Table
3) suggests that this form of emoji use is not a sustainable
strategy. To the contrary, we find that emoji use is by and
large negatively correlated with retweet count and in effect
diminishes attention via engagement.

Finally, H4 proposed that emoji and hashtags are primarily
affiliative gestures that call attention to individuals as bona fide
members of a given group. In light of the evidence, this strikes
us as the most plausible response to RQ2. For instance, Table
1, Figure 3, and Figure 4 all suggest that emoji are reliable
markers of group affiliation. Hence, it stands to reason that
they are also used as such. Further evidence in support of
this hypothesis holds to a certain extent in each of the four
analyses (see Table 3 and Table 4). Recall here that, even
though using emoji and hashtags in a given tweet generally
decreases the amount of attention awarded to that tweet,
doing so simultaneously decreases the prospect of receiving
more attention for future tweets.

Accordingly, it stands to reason that emoji and hashtags
are interpreted as affiliative gestures that impose an initial
cost on signaling one’s commitment to the group. Indeed,
as we noted in Figure S1 shows, there is a substantial overall retweet
penalty for both emoji and hashtags, with a correlation of
−0.73 and −0.66, respectively between number of items and
mean retweets. However, signaling does so with the payoff of
increasing one’s standing and following within that group. If
this is right, our results suggest an interesting tension between
H3 and H4. On the one hand, using emoji and hashtags
signals commitment to one’s group and increases the prospect
of receiving more attention from that group at some future mo-
ment. At the same time, it decreases the amount of attention
awarded to one’s present tweets.

In sum, we started by noting that hashtags can be un-
derstood as indexing mechanisms that systematically codify
certain topics under a common descriptor (23) and thus poten-
tially connect people who are interested in those topics (24).
Hence, we expected, and have now established, that hashtags
are a strong marker of group affiliation. This is especially
true for hashtags used by the conspiratorial wing of the Re-
actionary community (e.g., #qanon, #wwg1wga ) and the
K-Pop wing of the Booster community (e.g., #matchemil-
ion, #matchamillion). We note that the use of hashtags to
signal affiliation is not entirely foolproof. For instance, our
analyses confirm that the Boosters at one point briefly dra-
goond various Reactionary hashtags such as #bluelivesmatter
and #whitelivesmatter. However, trolling is not likely to be a
sustainable strategy in the long term, and we would expect
that the attention economy would quickly discard such efforts
(as in fact happened in this case).

At the same time, we are surprised to see that this indexing
function does not drive engagement. Contrary to previous
research (49), we conclude that hashtags are negatively cor-
related with retweet count and serve a primarily affiliative
function—at least as they are used in connection with the
Black Lives Matter movement.

With respect to emoji, our expectations are again only
partially confirmed. On the one hand, emoji such as the raised
fist (lifted fist) and exclamation marks (!!) do not succeed at drawing and directing attention to specific tweets.
Hence, emoji too can be understood as principally performing
a kind of affiliative function. Together, these results suggest

that emoji and hashtags play a complex role in the attention economy, operating at the level of both individual tweets and their authors.

Future research could, amongst other things, examine the ongoing activities of the communities studied in this paper. Examples include the November 2020 US Presidential Election; the 6 January 2021 insurrection by Reactionaries; and Twitter’s suspension of Donald Trump and purge of QAnon accounts.

Additionally, the use of emoji and hashtags in bios—as opposed to tweets—remains under-studied. One hypothesis prompted by the current research is that here too, emoji and hashtags would play an affirmative role. It would also be illuminating to test whether the affiliative use of emoji and hashtags generalizes across other topics (or is constrained to the Black Lives Matter movement), and to examine discourse on other platforms to test whether this use is confined to Twitter.

These directions for future research reflect some of the limitations of the current study, which does not cover the full multi-year history of the Black Lives Matter movement on Twitter, let alone on all platforms.

As protests and counter-protests continue to migrate to the digital space, the need to understand the use of emoji and hashtags in online activism becomes increasingly important. The current paper responds to this need and provides novel insights into the use of emoji and hashtags in online activism that we hope will be useful for further research.

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