Abstract—The media frequently describes the 2017 Charlottesville ‘Unite the Right’ rally as a turning point for the alt-right and white supremacist movements. Related research into social movements also suggests that the media attention and public discourse concerning the rally may have influenced the alt-right. Empirical evidence for these claims is largely lacking. The current study investigates potential effects of the rally by examining a dataset of 7,142 YouTube video transcripts from alt-right and progressive channels. We examine sentiment surrounding the ten most frequent keywords (single words and word pairs) in transcripts from each group, eight weeks before to eight weeks after the rally. In the majority of cases, no significant differences in sentiment were found within and between the alt-right and progressive groups, both pre- and post-Charlottesville. However, we did observe more negative sentiment trends surrounding ‘Bernie Sanders’ and ‘black people’ in the alt-right and progressive groups, respectively. We also observed more negative sentiment after the rally regarding ‘Democratic Party’ in the alt-right videos compared to the progressive videos. We suggest that the observed results potentially reflect minor changes in political sentiment before and after the rally, as well as differences in political sentiment between the alt-right and progressive groups in general.

Keywords—alt-right, charlottesville rally, sentiment analysis, youtube, quantitative text analysis

I. INTRODUCTION

On 11 and 12 August 2017, dozens of alt-right, white supremacist and neo-Nazi individuals descended on Charlottesville, Virginia. The event, known as the ‘Unite the Right’ rally, turned fatal on the second day when a white nationalist deliberately drove into a crowd of counter-protestors, resulting in the death of counter-protestor Heather Heyer and leaving several others injured (Hughes, 2018; Yan & Sayers, 2017). In recent years, the rise of the alt-right has been accompanied by several other acts of violence and terror attacks motivated by white supremacist ideologies, with 18 out of 34 extremist-related deaths in 2017 attributed to this group (Anti-Defamation League, 2017). In 2018, all 50 extremist murders in the United States were linked to right-wing extremism (Anti-Defamation League, 2018).

At the same time, alt-right ideologies have become widespread online. Their content is easily accessible through social media platforms, and ideas are amplified in echo chambers on extremist corners of the web (e.g., 4chan; Hine et al., 2017; and Gab; Zannettou et al., 2018). The video sharing platform YouTube has specifically been depicted by researchers and journalists as a breeding ground for the alt-right (Ellis, 2018; Lewis, 2018). Online political influencers adopt strategies of mainstream popular Youtubers to gain popularity, engaging in tactics for search engine optimisation and cultivating a relatable ‘underdog’ image (Lewis, 2018).

The alt-right is not defined by a central organisation (Hodge & Hallgrimsdottir, 2019), nor does it ‘offer a coherent or well-developed set of policy proposals’ (Hawley, 2018, p. 6). Instead, it has been referred to as a ‘mix of rightist online phenomena’ (Nagle, 2017, p. 15). Nonetheless, scholars have studied the alt-right as a social movement, following the definition of ‘a cluster of performances organised around a set of grievances or claims’ (Hodge & Hallgrimsdottir, 2019, p.2; see also Tilly, 1993). It has been argued that the alt-right, mainly through online activity, engages in promoting a shared identity, fostering commitment to a common cause, and proclaiming the ‘worthiness, unity, and size’ of its movement (Hodge & Hallgrimsdottir, 2019, p.2).

Elements of social movement theory propose that people engage in social identity performance, which refers to behaviour that serves to express the norms of the social group one aims to belong to (Klein, Spears, & Reicher, 2007; Simon, Trötschel, & Dähne, 2008). Such behaviour may serve different purposes, namely to affirm ones social identity, to conform to a social movement, to strengthen ones identity, or to mobilise others (Klein et al., 2007). Within the context of the alt-right, social identity performance may for example include using community-specific language (see e.g. Hine et al., 2017) or memes online (e.g. Pepe the Frog, a popular internet meme appropriated by the alt-right; Hawley, 2018; see also Hine et al., 2017), or to don symbols related to white nationalism in public.

After the Charlottesville rally, various media outlets have declared that ‘white nationalists are winning’ (Serwer, 2018), and ‘the genie is out of the bottle’ (Hughes, 2018). In addition, President Trump stated that there was ‘blame on both sides’ (Shear & Haberman, 2018), which prompted the suggestion that his claims ‘reinvigorated’ the alt-right movement (Shear & Haberman, 2018). In the aftermath of the rally, various reports also noted that white nationalists have entered mainstream conversation (Atkinson, 2018; Hughes, 2018) and some say they were aided in doing so by the Trump administration (Atkinson, 2018). Such claims potentially find some basis for support in the literature on the effect of media coverage and public discourse on social movements (Koopmans & Muis, 2009; Koopmans & Olzak, 2004).
Previous research on right wing violence in Germany suggests that positive as well as negative reactions from public figures to violent events may help to lend prominence to the movement (Koopmans & Olzak, 2004). That is, even if one aims to condemn a violent movement’s message, it is still necessary to at least partially reproduce the message (Koopmans & Olzak, 2004). By studying newspaper sources, this line of research suggested that discursive opportunities, summarised as public visibility, resonance, and legitimacy affected the behaviour of right-wing movements (measured in terms of violent events against different target groups; Koopmans & Olzak, 2004). Public visibility refers to the number of outlets reporting on the movement and the prominence of the movement’s message within those outlets (Koopmans & Olzak, 2004). Resonance is defined as the (positive or negative) reaction from public figures to the movement’s message as well as the associated ripple effect in the media (Koopmans & Olzak, 2004). Lastly, legitimacy involves the general public’s support of a message (Koopmans & Olzak, 2004). Similar discursive opportunities were also studied in relation to the rise in popularity of right-wing populist Pim Fortuyn in the Netherlands (Koopmans & Muis, 2009). In a similar vein, visibility (e.g. the extensive media coverage), resonance (e.g. responses to the rally from President Trump and other politicians), and legitimacy (e.g. subsequent protests and vigils denouncing the rally; Pelz, 2017) can be observed in the context of the alt-right and Charlottesville rally.

The effect of these discursive opportunities on the alt-right following the rally have received little attention within the academic literature thus far. If indeed the visibility of the alt-right increased following the rally, the message of the movement resonated in the media and public discourse, and the alt-right gained legitimacy through acknowledgement from opponents and the general public, we may expect to see changes in behaviour within the movement. Within the context of social identity performance, one may expect to see strengthened social identity consolidation within the alt-right movement as a result of the rally, President Trump’s comments, and the media coverage of the rally. After the rally, we might expect increased expression of norms from the alt-right movement, for example in the form of stronger endorsement or more extreme expressions of in-group ideology. As has been raised previously, such behaviour may serve to further strengthen the movement or mobilise others to join.

Empirical examinations of these possibilities are thus far lacking. Moreover, reactions to the rally have yet to be comprehensively examined for YouTube, seen as one of the hotbeds of alt-right online activity (Lewis, 2018). It can be argued that understanding the effect of external events on extremist groups on social media may be of particular interest to policy makers and security officials aiming to prevent or de-escalate violence. One way in which reactions to an event within a movement can be measured is by modelling language use of the movement across a time window surrounding an event of interest. In the following section, we discuss previous efforts at doing so.

II. LINGUISTIC EFFECTS OF EXOGENOUS EVENTS

The effect of extremism-related events on social media behaviour has been previously examined in a few cases. In a qualitative study of Twitter accounts of alt-right (Proud Boys & Oath Keepers) and far-left (Antifa) organisations in the six weeks leading up to the rally, it was observed that the two sides frequently targeted each other, framing the opposing group as the enemy (Klein, 2019). Manual examination of the tweets showed that the alt-right accounts frequently referred to ‘the left’ and ‘liberals’ as unpatriotic and communist, a clear example of the tension between alt-right supporters and left-leaning individuals and organisations. At the same time, the Antifa accounts dubbed the alt-right ‘suit and tie Nazis’. Furthermore, both the alt-right and far left groups incited violence in the weeks leading up to the Charlottesville rally and called for action among their supporters. A tweet from one of the alt-right groups read ‘The left is preparing lynch mobs to descend on the Unite The Right rally in Charlottesville, VA... This is going to be fun.’ (p. 311; Klein, 2019).

Beyond the Charlottesville rally, the effect of Islamist terrorism and Islamophobic attacks on hate speech has also been measured on Twitter and Reddit (Olteanu, Castillo, Boy, & Varshney, 2018). Using a dataset of 150 million messages spanning 19 months, hate speech was measured shortly after 13 extremist attacks and compared to predicted hate speech had no such event occurred. It was found that following Islamist terrorist attacks hate speech targeting Muslims, particularly those advocating violence, increased (Olteanu et al., 2018). At the same time, an increase in messages countering hate speech (e.g. defending Muslims) after Islamist terrorist attacks was observed (Olteanu et al., 2018). In contrast, following Islamophobic attacks, an increase in hate speech targeting Muslims was not found, with the exception of messages posted after the 2017 Finsbury Park Mosque attack (Olteanu et al., 2018).

Other investigations have examined changes in language over time in the context of political change. For example, hate speech and white nationalist rhetoric on Twitter have been examined during the 2016 election period in order to empirically examine wide-spread media coverage of the the rise in hate speech as a result of the Donald Trump’s divisive election campaign (Siegel et al., 2018). Using a dataset of 750 million tweets referring to Donald Trump and Hillary Clinton between June 15, 2015 (the day after the Trump candidacy was announced) and June 15, 2017, contrasted with a random sample of 400 million tweets from American Twitter users, hate speech and white nationalist language was measured with a dictionary approach using Hatebase, the Racial Slur Database, and the Anti-Defamation League’s database of white-nationalist language (Siegel et al., 2018). The tweets were examined by means of an interrupted time series analysis, to investigate whether hate speech increased during the Trump campaign or after Trump’s election. Although a spike in hate speech was observed in the Trump dataset following the imposed travel ban in early 2017, no significant lasting increase of hate speech or white nationalist language was observed in the Trump, Clinton, or random sample data (Siegel et al., 2018).

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2 See https://hatebase.org/, http://www.rslb.org/ and https://www.adl.org/education-and-resources/resource-knowledge-base/hate-symbols
III. CURRENT STUDY

The present study takes a closer look at a population of alt-right content creators (hereafter, ‘alternative group’) by examining a new dataset of YouTube video transcripts extracted from channels by individuals ‘who range in ideology from mainstream libertarian to openly white nationalist’ (Ellis, 2018). These video transcripts are contrasted with those extracted from YouTube channels whose political sentiment can be considered more progressive (hereafter, ‘progressive group’), what might be considered ‘the left’. This paper centres around the question whether we can observe the effect of the Charlottesville rally on language use on YouTube in the alternative and progressive groups. We specifically examine language in terms of sentiment regarding specific frequent words that appear in the video transcripts. In other words, we study whether the alternative and progressive groups speak positively or negative about specific concepts, and how these sentiments develop over time before and after the rally.

Since this paper is among the first to examine language use before and after the rally, we do not postulate any directional hypotheses about changes in language use (e.g. more positive or negative language use regarding specific concepts). However, in light of the social movement and social identity performance literature, we do expect to see changes in social identity performance after the rally reflected in language use on YouTube. The rationale for examining changes after the rally is further derived from previous research on social movements examining the effects of discourse opportunities on the behaviour of social movements (Koopmans & Muis, 2009; Koopmans & Olzak, 2004). We include progressive channels in our analysis to examine whether this opposing group reacts to changes in social identity performance on part of the alternative group, or perhaps exhibits changes in social identity performance itself as a consequence of the violent rally. In short, the current study examines the following questions:

1. Is there difference in sentiment surrounding frequent keywords before versus after the Charlottesville rally, in both the alternative and progressive YouTube channels?
2. Is there a difference in sentiment surrounding frequent keywords in alternative versus progressive YouTube channels, both before and after Charlottesville?

In other words, this study examines the sentiment surrounding frequent keywords both within and between the alternative and progressive channels. This analysis looks at a time-frame of sixteen weeks surrounding Charlottesville, in order to assess potential effects of the rally.

IV. DATA

A. Channel selection

YouTube channels for analysis were selected from two main sources. Firstly, we drew from the list of 65 YouTube users referred to as the ‘Alternative Influence Network’ in the 2018 Data & Society report on political influencers (Lewis, 2018). Based on this list, we searched for a designated YouTube channel for each individual. If an individual did not have a designated YouTube channel or their channel was no longer available, we searched for the individual’s name through the YouTube search function. For example, videos featuring Alex Jones (who no longer has a designated channel) were obtained by means of the search query ‘alex jones full show’. This first group of alternative YouTube channels consisted of 56 channels and search queries to be considered for transcript retrieval. The second source for video selection were two online lists of progressive YouTube channels. Since the lists referred to specific existing channels, search queries for specific persons were not necessary. In total, 13 progressive channels were considered for transcript retrieval. For all channels and search queries, we retrieved the URLs for all available videos.

B. Transcript retrieval

The method for retrieving YouTube video transcripts follows the procedure of related research (Kleinberg, Mozes, & van der Vegt, 2018; Soldner et al., 2019). In order to retrieve the transcripts, a Python script was written that makes use of www.downsub.com, a website that provides YouTube transcripts when the video URL is entered. The transcripts downloaded through the script were either automatically generated on YouTube or manually added by the YouTube user. In some cases, no transcript was available, because users can also disable transcript availability. The resulting collection of transcripts were XML-encoded, with time-stamped word sequences (e.g. 00:05:00:07 “Hello everyone!”). XML-tags and time-stamps were removed, resulting in a single string for each video transcript.

C. Data cleaning

Videos that contained fewer than 100 words were not considered for analysis. Each video was checked for English language, and was excluded if it contained fewer than 50% English words. Videos were also excluded if they contained fewer than 90% ASCII characters. The video transcripts were made lower-case and cleaned by removing stop-words with the tidytext R package (Silge & Robinson, 2019), as well as unnecessary whitespace and punctuation with the tm (Feinerer & Hornik, 2018) and qdap (Rinker, 2019) R packages.

D. Sample

For the purpose of analysing potential effects of the rally on sentiment surrounding specific keywords, we selected videos from the dataset that were posted between eight weeks prior to the Charlottesville rally, to eight weeks after the rally. This resulted in sixteen time-segments for the progressive and alternative groups. The division of videos per time-segment as well as the dates for each are depicted in Figure 1. Descriptive statistics for this sample are given in Table 1.

| TABLE I. DESCRIPTIVE STATISTICS SAMPLE (MEAN, SD) |
|----------------------------------|------------------|------------------|
| Alternative                       | Progressive      |
| ---------------------------------|------------------|------------------|
| Total number of videos            | 2,684            | 4,458            |
| Total word count                  | 3,868,744        | 2,684,703        |
| Mean word count (SD)              | 1,448 (1,612)    | 632 (860)        |
| Mean view count (SD)              | 120,639 (234,513)| 24,787 (47,468) |

2 https://datasociety.net/wp-content/uploads/2018/09/DS_Alternative_Influence.pdf
3 http://the2020progressive.com/top-13-progressive-news-shows-youtube/ and https://medium.com/@tejazz89/top-5-youtube-channels-to-follow-if-you-are-a-true-progressive-e22ab78d58f
V. METHOD

A. KEYWORD SELECTION

To assess possible effects of the rally on sentiment surrounding specific keywords in the video transcripts, we extract the ten unigrams and bigrams with the highest proportional occurrence in both groups (frequency of n-gram divided by total tokens in the corpus). Only adjectives and nouns were considered because we consider these parts-of-speech to convey the most meaning. If two n-grams within the top ten represented the same concept (e.g., ‘donald trump’ and ‘president trump’) the n-gram with the higher proportion was selected and the duplicate(s) were not considered for selection. The final lists of unigrams and bigrams were used as keywords to extract ‘keywords in context’ by means of the quanteda R package (Benoit et al., 2018). This procedure looks for each occurrence of a keyword in every video transcript, then extracts it along with a window of five words preceding and five words following each keyword, representing the context around the keyword instance. For example, the context ‘counsel robert muller investigating president’ may precede the keyword ‘trump’, followed by ‘obstruction justice investigating trumps son-in-law’ (note that the stop-words have been removed here). Thereafter, a sentiment analysis is performed on the context windows (the keyword in question is excluded from sentiment analysis). The sentiment analysis is performed by means of the sentimentr R package (Rinker, 2019), which takes valence shifters into account. The sentiment analysis is repeated for all time-segments and in both progressive and alternative groups. Based on this, the average sentiment scores for the context around each keyword are computed for each time-segment. In addition to this, we also computed the average sentiment for each keyword during the Charlottesville rally following the same procedure.

Once weekly sentiment scores have been computed for each keyword, average sentiment was compared by means of independent sample t-tests between 1) pre-Charlottesville and post-Charlottesville, for both alternative and progressive groups separately, and 2) pre-Charlottesville in the progressive versus alternative group, and post-Charlottesville in the progressive versus alternative groups. See Figure 2 for a graphic representation of the comparisons. Finally, a Bonferroni correction was applied to make up for the two comparisons for each time segment, resulting in an alpha level of 0.05/4 = 0.0125.

In addition to testing differences in average sentiment, differences in slope for the same four comparisons (see Figure 2) were computed. This procedure enables us to assess whether there was a difference in sentiment trends between and within groups. Slope comparisons were performed by computing z-scores for the differences in slope in line with the formula below (Paternoster, Brame, Mazerolle, & Piquero, 1998).

Formula 1. Z-score for differences in slope

\[ z = \frac{b_1 - b_2}{\sqrt{SEb_1^2 + SEb_2^2}} \]

Where \( b_1 \) and \( b_2 \) represent the slopes for the time segments to be compared, and \( SEb_1 \) and \( SEb_2 \) the standard errors of the respective slopes. Again, a Bonferroni correction was applied resulting in an alpha level of 0.05/4 = 0.0125.

VI. RESULTS

A. KEYWORD SELECTION

A list of unigrams and bigrams with the highest proportional occurrence in the total progressive and alternative groups was generated, and the first 10 nouns and adjectives were selected to serve as keywords across all time-segments. Since there was a large degree of overlap between the two groups, this resulted in a list of 14 total unigrams and 13 total bigrams depicted in Table 2. Although the table presents n-gram frequencies within both groups, the selection of n-grams was done based on the proportions of occurrence (frequency of n-gram divided by total tokens in each group).

### TABLE II. UNIGRAM AND BIGRAM FREQUENCIES

| Unigrams | Alt. | Progr. | Bigrams | Alt. | Progr. |
|----------|------|--------|---------|------|--------|
| people*  | 55662| 42641  | donald trump* | 4500 | 7157  |
| trump*   | 15418| 21487  | health care*  | 2167 | 4025  |
| time*    | 14290| 10663  | bernie sanders* | 1871| 3215  |
| white*   | 8486 | 6248   | hillary clinton* | 1506| 2142  |
| care*    | 6388 | 8396   | puerto rico*  | 1142| 1711  |
| country* | 6153 | 7441   | white house*  | 1100| 1816  |
| money*   | 6754 | 7179   | black people* | 1123| 591   |
| guy*     | 7772 | 5295   | north korea*  | 1048| 1583  |
| party*   | 4519 | 6837   | health insurance* | 552| 1279  |
| talk*    | 8814 | 6695   | free speech*  | 1091| 644   |
| shit*    | 6724 | 3330   | climate change* | 982 | 1235  |
| health*  | 3610 | 6546   | white people* | 1064| 397   |
| stuff*   | 6407 | 3665   |                     |      |        |

* The superscript ‘*’ denotes the n-gram occurred in the top 10 of both the progressive and alternative groups, ‘p’ means it occurred in the top 10 of the progressive group, and ‘a’ in the alternative group (all in terms of proportions).
After establishing the context around each keyword (five words pre- and post-keyword) in all videos across the progressive and alternative groups, the average sentiment score was computed for the context surrounding each keyword for each time-segment, as well as the average score during the Charlottesville rally. We show plots with sentiment scores per time-segment for “people” (Figure 3), “trump” (Figure 4), “bernie sanders” (Figure 5), “black people” (Figure 6), and “democratic party” (Figure 7). Each figure shows sentiment scores per week for the alternative (red) and progressive (blue) group. Trendlines (dashed blue and red) are depicted for the pre- and post- Charlottesville measurements separately. The dashed black line in the centre represents the Charlottesville rally. Remaining plots are available on the Open Science Framework:

https://osf.io/yedt7/?view_only=ec235f877d24731ad5140e261c74cdd

B. Unigram differences pre- and post-Charlottesville

For both the alternative and progressive groups, average sentiment was compared between pre-and post-Charlottesville measurements. Table 3 shows average sentiment values, as well as the results of the t-tests within both groups. We see a significant difference in sentiment surrounding the unigram ‘people’ in the alternative group (p < 0.0125), with post-Charlottesville sentiment being more negative than pre-Charlottesville sentiment.

In addition to this, time-series models were built for both the pre- and post-Charlottesville sentiment measures of each unigram (four models per unigram). Table 4 shows the pre- and post-Charlottesville slopes for both groups, as well as a z-score and associated p-value representing the difference between the pre- and post-Charlottesville slopes for each unigram. We do not see any significant differences in slope between pre- and post-Charlottesville measurements in either groups (p > 0.0125).
### TABLE III. WITHIN GROUP PRE- AND POST-CHARLOTTESVILLE MEAN UNIGRAM SENTIMENT AND SENTIMENT DIFFERENCES

| Unigram | Alternative | Progressive |
|---------|-------------|-------------|
|         | pre | post | diff | t | p   | pre | post | diff | t | p   |
| people  | -0.03 | -0.04 | -0.01 | -3.27 | **0.006** | -0.03 | -0.04 | -0.01 | -2.21 | 0.051 |
| trump   | -0.04 | -0.04 | 0.00 | 0.06 | 0.954 | -0.03 | -0.04 | -0.01 | -1.31 | 0.227 |
| time    | -0.02 | -0.02 | 0.00 | 0.29 | 0.773 | -0.02 | -0.03 | 0.00 | -0.53 | 0.607 |
| fucking | -0.14 | -0.16 | -0.03 | -2.44 | 0.032 | -0.13 | -0.14 | -0.01 | -1.15 | 0.268 |
| white   | -0.04 | -0.04 | 0.00 | -0.37 | 0.716 | -0.02 | -0.03 | -0.01 | -0.76 | 0.459 |
| care    | 0.03  | 0.03  | -0.01 | -0.61 | 0.555 | 0.05  | 0.04  | 0.00  | -0.22 | 0.829 |
| country | -0.01 | -0.03 | -0.03 | -2.22 | 0.045 | -0.01 | -0.03 | -0.01 | -1.54 | 0.148 |
| money   | 0.01  | 0.02  | 0.01  | 0.89  | 0.390 | 0.03  | 0.03  | 0.01  | 0.96  | 0.355 |
| guy     | -0.04 | -0.04 | 0.00 | 0.09 | 0.934 | -0.04 | -0.05 | 0.00 | -0.23 | 0.826 |
| party   | -0.03 | -0.02 | 0.00 | 0.32 | 0.752 | -0.01 | -0.01 | -0.01 | -0.67 | 0.519 |
| talk    | 0.00  | 0.00  | -0.01 | -0.71 | 0.491 | 0.01  | -0.01 | -0.02 | -1.95 | 0.078 |
| shit    | -0.11 | -0.13 | -0.01 | -1.28 | 0.227 | -0.12 | -0.11 | 0.00 | 0.26  | 0.797 |
| health  | 0.13  | 0.10  | -0.03 | -0.99 | 0.347 | 0.15  | 0.15  | 0.00  | -0.18 | 0.859 |
| stuff   | -0.01 | -0.02 | -0.01 | -1.09 | 0.297 | -0.03 | -0.01 | 0.02  | 2.07  | 0.057 |

* Differences represent: bhpost - bpre (a negative value indicates that the sentiment post-Charlottesville is more negative than pre-Charlottesville)

### TABLE IV. WITHIN GROUP PRE- AND POST-CHARLOTTESVILLE UNIGRAM SLOPES AND SLOPE DIFFERENCES

| Unigram | Alternative | Progressive |
|---------|-------------|-------------|
|         | pre | post | diff | z  | p   | pre | post | diff | z  | p   |
| people  | -0.01 | 0.03  | 0.04  | 0.41 | 0.680 | 0.16 | 0.16  | 0.00 | 0.01 | 0.996 |
| trump   | 0.10  | 0.16  | 0.06  | 0.28 | 0.776 | -0.01 | 0.04 | 0.05  | 0.32 | 0.752 |
| time    | -0.02 | 0.06  | 0.07  | 0.44 | 0.657 | 0.28 | 0.17 | -0.11 | -0.64 | 0.523 |
| fucking | 0.20  | 0.00  | -0.20 | -0.80 | 0.421 | -0.02 | -0.14 | -0.12 | -0.48 | 0.630 |
| white   | -0.15 | 0.20  | 0.35  | 1.86 | 0.063 | 0.31 | 0.31 | 0.00  | -0.01 | 0.995 |
| care    | -0.01 | -0.08 | -0.07 | -0.28 | 0.777 | 0.07 | 0.17 | 0.10  | 0.60  | 0.546 |
| country | 0.27  | 0.46  | 0.19  | 0.92 | 0.357 | 0.21 | 0.08 | -0.12 | -0.65 | 0.516 |
| money   | -0.03 | 0.08  | 0.11  | 0.60 | 0.546 | -0.04 | 0.16 | 0.21  | 1.16  | 0.247 |
| guy     | 0.06  | 0.23  | 0.17  | 1.17 | 0.243 | 0.27 | 0.02 | -0.25 | -0.79 | 0.430 |
| party   | 0.13  | 0.35  | 0.22  | 0.65 | 0.518 | 0.10 | -0.07 | -0.17 | -0.74 | 0.460 |
| talk    | 0.15  | 0.26  | 0.11  | 0.65 | 0.516 | 0.19 | 0.24 | 0.05  | 0.23  | 0.822 |
| shit    | 0.21  | 0.13  | -0.08 | -0.31 | 0.756 | 0.13 | 0.06 | -0.07 | -0.22 | 0.830 |
| health  | 0.11  | -0.25 | -0.36 | -0.50 | 0.618 | 0.30 | -0.17 | -0.47 | -1.22 | 0.223 |
| stuff   | 0.17  | 0.16  | -0.01 | -0.06 | 0.949 | 0.04 | 0.18 | 0.14  | 0.54  | 0.586 |

* Differences represent: bpost - bpre (a negative value indicates that the slope post-Charlottesville decreased in contrast to the slope pre-Charlottesville)
C. Unigram differences alternative versus progressive group

We also compared average sentiment for each unigram between the progressive and alternative groups, both pre- and post-Charlottesville. Table 5 shows average sentiment values, as well as the results of the t-tests between both groups. We do not see any significant differences in average unigram sentiment between groups \( p > 0.0125 \).

The slopes of the timeseries models for each unigram were also compared between the progressive and alternative groups, both pre- and post-Charlottesville. Table 6 shows the measures of differences for each unigram between the progressive and alternative groups within the pre-Charlottesville time-segments, as well as the difference between the two groups within the post-Charlottesville time-segments. Differences in slope were computed by subtracting the slope of the alternative groups from the slope of the segments. Differences in slope were computed by subtracting the slope of the alternative groups from the slope of the segments.

### Table V. Between-group pre- and post-Charlottesville unigram sentiment and sentiment difference

| Unigram | Pre-Charlottesville | Post-Charlottesville | diff | t | p | diff | t | p |
|---------|---------------------|----------------------|------|---|---|------|---|---|
| people  | 0.00                | 1.19                 | 0.19 | 0.00| 0.33| 0.752 |   |    |
| trump   | 0.01                | 1.16                 | 1.15 | 0.00| -0.10| 0.925 |   |    |
| time    | 0.00                | -0.18                | -0.18| 0.00| -1.08| 0.300 |   |    |
| fucking | 0.01                | 1.08                 | 1.07 | 0.02| 2.01 | 0.065 |   |    |
| white   | 0.02                | 1.80                 | 1.78 | 0.01| 0.84 | 0.418 |   |    |
| care    | 0.01                | 2.32                 | 2.31 | 0.02| 1.73 | 0.111 |   |    |
| country | -0.01               | -0.91                | -0.90 | 0.00| 0.41 | 0.690 |   |    |
| money   | 0.02                | 2.02                 | 2.01 | 0.02| 2.12 | 0.052 |   |    |
| guy     | 0.00                | -0.07                | -0.07| 0.00| -0.32| 0.756 |   |    |
| party   | 0.02                | 2.33                 | 2.32 | 0.01| 0.82 | 0.425 |   |    |
| talk    | 0.01                | 1.27                 | 1.26 | 0.02| 0.47 | 0.644 |   |    |
| shit    | 0.00                | -0.02                | -0.02| 0.02| 1.52 | 0.155 |   |    |
| health  | 0.02                | 1.52                 | 1.51 | 0.05| 1.53 | 0.154 |   |    |
| stuff   | -0.02               | -2.50                | -2.49| 0.01| 0.97 | 0.347 |   |    |

* Differences represent: \( b_{alternative} - b_{progressive} \) (a negative value indicates the sentiment for the alternative group is more positive than that of the progressive group)

### Table VI. Between-group pre- and post-Charlottesville unigram slopes and slope differences

| Unigram | Pre-Charlottesville | Post-Charlottesville | diff | z | p | diff | z | p |
|---------|---------------------|----------------------|------|---|---|------|---|---|
| people  | 0.16                | 2.21                 | 2.05 | 0.13| 0.85 | 0.393 |   |    |
| trump   | -0.11               | -0.64                | -0.53| -0.12| -0.60| 0.545 |   |    |
| time    | 0.30                | 1.80                 | 1.49 | 0.12| 0.68 | 0.494 |   |    |
| fucking | -0.22               | -1.02                | -0.80| -0.14| -0.50| 0.619 |   |    |
| white   | 0.46                | 2.29                 | 2.13 | 0.11| 0.40 | 0.691 |   |    |
| care    | 0.07                | 0.48                 | 0.31 | 0.24| 0.93 | 0.354 |   |    |
| country | -0.06               | -0.29                | -0.23| -0.12| -0.37| 0.955 |   |    |
| money   | -0.02               | -0.10                | -0.08| 0.08| 0.47 | 0.637 |   |    |
| guy     | 0.21                | 1.37                 | 1.16 | -0.21| -0.68| 0.495 |   |    |
| party   | -0.03               | -0.14                | -0.03| -0.43| -1.28| 0.201 |   |    |
| talk    | 0.04                | 0.28                 | 0.24 | -0.02| -0.08| 0.934 |   |    |
| shit    | -0.09               | -0.29                | -0.20| -0.07| -0.26| 0.794 |   |    |
| health  | 0.19                | 0.61                 | 0.42 | 0.07| 0.10 | 0.920 |   |    |
| stuff   | -0.13               | -0.66                | -0.53| 0.02| 0.08 | 0.937 |   |    |

* Differences represent: \( b_{alternative} - b_{progressive} \)

D. Bigram differences pre- and post-Charlottesville

Following the same procedure as with the unigrams, average bigram sentiment was compared between pre-and post-Charlottesville measurements for both groups. In Table 7, we see a significant difference in sentiment surrounding the bigram ‘climate change’ in the progressive group \( p < 0.0125 \), with post-Charlottesville sentiment being more negative than pre-Charlottesville sentiment.

We also built timeseries models for pre- and post-Charlottesville sentiment measures of each bigram (four models per bigram). Table 8 shows the pre- and post-Charlottesville slopes and slope differences within each group. In the alternative group, we see a significant difference between pre- and post-Charlottesville measurements surrounding ‘bernie sanders’, with a positive trend pre-Charlottesville and a negative trend post-Charlottesville (see also Figure 5). Note that the positive trend does not necessarily imply positive sentiment, since average sentiment pre-Charlottesville was -0.01 (Table 7). In the progressive group, we see a significantly more negative sentiment slope post-Charlottesville surrounding ‘black people’, compared to a positive trend pre-Charlottesville \( p < 0.0125 \). Trend lines are also shown in Figure 6.

E. Bigram differences alternative versus progressive group

We also compared average sentiment for each bigram between the progressive and alternative groups, both pre- and post-Charlottesville. Table 9 shows average sentiment values, as well as the results of the t-tests between both groups. We see differences in sentiment between groups for ‘democratic party’ post-Charlottesville, with more negative sentiment in the alternative group than the progressive group \( p < 0.0125 \).

We also computed the differences in slope between the progressive and alternative groups for each bigram within the same time window (pre- or post-Charlottesville), depicted in Table 10. Pre-Charlottesville, the progressive group shows a significantly larger slope for ‘black people’ \( p < 0.0125 \), see also Figure 6). Post-Charlottesville, we observe a significantly more negative slope in the alternative group surrounding ‘bernie sanders’ than in the progressive group \( p < 0.0125 \), see also Figure 5).
### TABLE VII. WITHIN-GROUP PRE- AND POST-CHARLOTTESVILLE MEAN
BIVARAG SENTIMENT AND SENTIMENT DIFFERENCES

| Unigram                | Alternative | Progressive |
|------------------------|-------------|-------------|
|                        | pre | post | diff | t  | p   | pre | post | diff | t  | p   |
| donald trump           | -0.05| -0.05| 0.00  | -0.01| 0.993| -0.03| -0.04| -0.01| -1.08| 0.302|
| health care            | 0.06 | 0.03 | -0.03 | -0.82| 0.435| 0.04  | 0.05  | 0.01  | 0.86 | 0.406|
| bernie sanders         | -0.01| -0.04| -0.03| -0.94| 0.363| -0.01| 0.00  | 0.02  | 1.31 | 0.210|
| democratic party       | -0.06| -0.07| -0.01| -0.35| 0.733| -0.01| -0.01| 0.00  | -0.10| 0.918|
| hillary clinton        | -0.05| -0.07| -0.01| -0.38| 0.713| -0.05| -0.02| 0.02  | 2.53 | 0.026|
| white house            | -0.02| 0.01 | 0.01  | 0.50 | 0.629| -0.01| 0.00  | 0.00  | 0.37 | 0.720|
| black people           | -0.10| -0.11| 0.00  | -0.25| 0.807| -0.12| -0.08| 0.04  | 1.18 | 0.263|
| north korea            | -0.05| -0.06| -0.01| -0.17| 0.866| -0.07| -0.12| -0.05| -1.78| 0.108|
| health insurance       | -0.02| 0.00 | 0.02  | 0.26 | 0.800| 0.00  | 0.00  | -0.01| -0.23| 0.825|
| free speech            | 0.02 | 0.04 | 0.02  | 0.99 | 0.343| 0.01  | -0.01| -0.02  | -0.55| 0.590|
| climate change         | 0.00 | -0.06| -0.07| -1.44| 0.185| -0.02| -0.07| -0.06  | -3.06| 0.011*|
| white people           | -0.07| -0.07| 0.00  | -0.25| 0.808| -0.04| -0.03| 0.01  | 0.41 | 0.690|

### TABLE VIII. WITHIN-GROUP PRE- AND POST-CHARLOTTESVILLE BIVARAG SLOPE DIFERENCES

| Word                   | Alternative | Progressive |
|------------------------|-------------|-------------|
|                        | pre | post | diff | t   | p   | pre | post | diff | t   | p   |
| donald trump           | 0.27 | 0.35 | 0.08  | 0.20 | 0.839| 0.06 | 0.05 | -0.01| -0.05| 0.963|
| health care            | 0.72 | -0.31| -1.03| -1.11| 0.265| 0.33 | 0.04 | -0.29| -1.11| 0.265|
| bernie sanders         | 0.88 | -1.11| -1.99| -3.05| 0.002*| 0.32| 0.16 | -0.15| -0.61| 0.544|
| democratic party       | -0.26| -0.03| 0.23  | 0.30 | 0.764| 0.37 | 0.09 | -0.29| -0.93| 0.350|
| hillary clinton        | 0.39 | 0.66 | 0.27  | 0.29 | 0.771| -0.09| 0.18 | 0.27 | 1.22 | 0.221|
| white house            | -0.38| 0.47 | 0.85  | 1.44 | 0.151| 0.05 | 0.13 | 0.08 | 0.35 | 0.726|
| black people           | -0.13| 0.19 | 0.32  | 0.85 | 0.396| 1.39 | -0.28| -1.66| -2.67| 0.008*|
| north korea            | 0.21 | -0.27| -0.48| -0.45| 0.651| -0.51| -0.07| 0.44 | 0.62 | 0.538|
| health insurance       | -0.03| -1.01| -0.97| -0.51| 0.613| 0.01 | 0.16 | 0.15 | 0.26 | 0.795|
| free speech            | 0.23 | 0.18 | -0.05| -0.12| 0.905| -0.84| -0.13| 0.71 | 0.69 | 0.488|
| climate change         | -0.50| -0.90| -0.40| -0.39| 0.697| -0.24| 0.57 | 0.81 | 2.14 | 0.032|
| white people           | -0.36| 0.16 | 0.52  | 1.64 | 0.101| 0.33 | -0.21| -0.53| -0.70| 0.483|

### TABLE IX. BETWEEN-GROUP PRE- AND POST-CHARLOTTESVILLE BIVARAG SENTIMENT AND SENTIMENT DIFFERENCES

| Word                   | Pre-Charlottesville | Post-Charlottesville |
|------------------------|---------------------|----------------------|
|                        | diff | t   | p   | diff | t   | p   |
| donald trump           | 0.01 | 1.00 | 0.344| 0.01 | 0.52 | 0.612|
| health care            | -0.02| -1.24| 0.242| 0.02 | 0.56 | 0.588|
| bernie sanders         | 0.00 | -0.17| 0.868| 0.04 | 1.73 | 0.117|
| democratic party       | 0.05 | 1.55 | 0.158| 0.06 | 3.30 | 0.006*|
| hillary clinton        | 0.00 | 0.05 | 0.958| 0.04 | 1.09 | 0.310|
| white house            | 0.01 | 1.19 | 0.262| 0.01 | 0.21 | 0.842|
| black people           | -0.02| -0.64| 0.534| 0.02 | 1.24 | 0.245|
| north korea            | -0.02| -0.52| 0.611| -0.06| -1.51| 0.170|
| health insurance       | 0.02 | 0.53 | 0.609| 0.00 | -0.01| 0.993|
| free speech            | -0.01| -0.38| 0.707| -0.05| -1.47| 0.181|
| climate change         | -0.02| -1.17| 0.264| -0.01| -0.22| 0.833|
| white people           | 0.03 | 1.15 | 0.278| 0.05 | 2.30 | 0.044|
### VII. DISCUSSION

The present study assessed whether an effect of the Charlottesville Unite the Right rally can be observed on alternative and progressive YouTube video channels. We expected to see differences in language use after Charlottesville due to the discursive opportunities lent to the alt-right movement as a result of the rally, potentially resulting in increased social identity performance. Specifically, we extracted frequent n-grams and examined the sentiment surrounding each to see if there was an effect of the rally on sentiment relating to specific concepts. First, we examined whether there was a difference in sentiment surrounding frequent unigrams and bigrams before and after the Charlottesville rally, in both the alternative and progressive YouTube channels separately. At the unigram level, we mostly did not observe any differences in average sentiment or sentiment trends, suggesting that sentiment regarding the keywords examined did not change significantly before and after the rally. We only observed more negative average sentiment surrounding ‘people’ after the rally in the alternative group. Possibly, this shows a more negative outlook on ‘people’ after the rally, but unigrams unfortunately do not provide enough context for us to draw such conclusions. Indeed, the unigram ‘people’ may occur as ‘black people’, ‘rich people’ or ‘white people’, which may be referred to with very different sentiments within and across videos. Therefore, effects of the rally may have been averaged out due to different contexts, suggesting that unigrams were perhaps less insightful than bigrams for the purpose of this study. Therefore, we turn to bigrams to gain a deeper insight into the transcripts.

When comparing pre- and post-Charlottesville average bigram sentiment in both groups separately, we only observed more negative average sentiment after the rally for ‘climate change’ in the progressive group. However, it is unclear to what extent the rally in particular may have influenced this change in mean sentiment. In terms of sentiment trends, differences were observed for the bigrams ‘bernie sanders’ and ‘black people’. Regarding ‘bernie sanders’, we see that the slope surrounding this bigram in the alternative group significantly changes from a positive slope (albeit negative average sentiment) to a negative slope (still negative average sentiment) after the rally. Interestingly, Bernie Sanders made strong statements on the rally, stating: ‘The white nationalist demonstration in Charlottesville, Virginia, is a reprehensible display of racism and hatred […] I am disgusted by the news […] While this incident is alarming, it is not surprising […].’ However, a detailed content analysis of the videos referring to Bernie Sanders post-Charlottesville will be needed to confirm whether there is an explicit relationship between his statements and the sentiment observed in the alternative group. Nevertheless, this result potentially reflects the concept of resonance as a discourse opportunity (Koopmans & Olzak, 2004), where negative attention from a public actor further disseminates a movement’s message, resulting in potential behavior changes on part of the social movement. Furthermore, we also observed a change from a positive slope (albeit negative average sentiment) to a negative slope (still negative average sentiment) in the progressive group for the bigram ‘black people’. This result could perhaps be explained by an increased sense of threat towards black people from white supremacists post-Charlottesville. Again, follow-up research will be needed to examine whether this is also explicitly stated in the context of ‘black people’ in post-Charlottesville videos.

We also investigated whether there was a difference in sentiment surrounding important unigrams and bigrams in alternative versus progressive YouTube channels, both before and after Charlottesville separately. We observed no significant differences between groups in average sentiment surrounding unigrams, neither before nor after the rally. Again, the contextual ambiguity of unigrams may explain this. In the bigram tests, we saw more negative average sentiment for ‘democratic party’ in the alternative group versus the progressive group after the rally, which may be explained through general political sentiment in both groups. Indeed, the alternative group may be more likely to harbour negative sentiment towards the Democrats than the progressive group. In terms of sentiment trends, we observed a difference between the two groups for the bigram ‘bernie sanders’, with progressive videos showing a higher slope than alternative videos post-Charlottesville. Again, this may have to do with comments made by Sanders after the rally and how they were received in the progressive group versus the alternative group.

In short, the current results suggest that there are some minor differences in language use both within and between alternative and progressive groups in a sixteen week timeframe around the Charlottesville rally. Results possibly reflect political sentiment before and after the rally, as well as potential differences in general political sentiment between both groups. However, we acknowledge additional research will be needed to examine the precise contexts that give rise to positive and negative sentiment observed in the present study.

#### A. Limitations

The current study is not without limitations. First, the data sources that we have drawn on for the YouTube videos were unbalanced in nature. Although the progressive sample consisted of more videos than the alternative sample, the progressive sample was made up of fewer channels than the alternative sample. This was due to the fact that we were able to attain a large list of alternative YouTube channels through the Data & Society report, but no similar report or collection exists for progressive YouTube channels. Furthermore, the two groups also differed in terms of view counts and video length, both factors which may have impacted on language use and sentiment. Indeed, previous research has raised the

| Word | Pre-Charlottesville | Post-Charlottesville |
|------|---------------------|----------------------|
| diff | z       | p       | diff | z       | p       |
| donald | -0.21 | -0.62 | 0.533 | -0.30 | -1.04 | 0.300 |
| trump | -0.39 | -1.46 | 0.145 | 0.35 | 0.38 | 0.701 |
| health care | -0.56 | -1.02 | 0.307 | 1.27 | 2.95 | 0.003* |
| bernie sanders | 0.63 | 0.88 | 0.378 | 0.11 | 0.27 | 0.787 |
| democratic party | -0.49 | -1.33 | 0.182 | -0.48 | -0.55 | 0.582 |
| hillary clinton | 0.43 | 1.68 | 0.093 | -0.34 | -0.58 | 0.562 |
| black people | 1.52 | 2.65 | **0.008** | -0.46 | -1.04 | 0.299 |
| north korea | -0.72 | -0.93 | 0.350 | 0.21 | 0.20 | 0.840 |
| health insurance | 0.04 | 0.04 | 0.970 | 1.16 | 0.69 | 0.491 |
| free speech | -1.07 | -1.65 | 0.099 | -0.31 | -0.34 | 0.734 |
| climate change | 0.26 | 0.82 | 0.414 | 1.47 | 1.41 | 0.160 |
| white people | 0.69 | 1.05 | 0.292 | -0.37 | -0.73 | 0.467 |

TABLE X. BETWEEN-GROUP PRE- AND POST-CHARLOTTESVILLE BIGRAM SLOPES AND SLOPE DIFFERENCES
possibility of external factors, such as gender (Kleinberg, Mozes, & van der Vegt, 2018) and political leaning (Soldner et al., 2019), influencing sentiment styles in YouTube videos. In addition, while the alternative channels were drawn from a research report, the list of progressive channels were drawn from user-generated online lists. Future research may be aimed at curating an expert-verified or crowd-sourced dataset of channels with different political biases.

Regarding the keyword in context analysis, no consensus seems to exist in the literature as to the length of the keyword windows. We adhered to the default setting in the quanteda R package (Benoit et al., 2018) of five words pre- and post-keyword, but would encourage others to use the code and data of the current study to explore variations of these parameters. Furthermore, the video transcripts contained no punctuation in part due to the nature of automatic transcriptions, which may have additionally impacted the sentiment analysis. That is, the window surrounding a keyword may include a word that belongs to what would be perceived as a previous or next sentence or phrase. Since the sequence of video transcripts were represented as a single string per time-segment, a word from a previous or next video may have been included in the keyword context as well. Alternatively, a word that may have been a valence shifter may not have been included in the context windows. Although these matters may have had an impact on the sentiment analysis, this is unfortunately unavoidable due to unpunctuated nature of the transcripts.

Lastly, the sentiment scores were aggregated over each week. These aggregations will inevitably have resulted in loss of information. However, due to the nature of the dataset this particular unit of measurement were necessary. Since we sought videos with specific keywords in their transcripts, the sample was narrowed down significantly. That is, to analyse the sentiment surrounding ‘hillary clinton’, we could only make use of videos in which ‘hillary clinton’ was mentioned. As a result, some time-segments did not have a video with the keyword available on each day for either groups. Therefore, we could not construct daily time series, and resorted to weekly averages instead.

B. Outlook

Future research may focus on extending the present approach to measuring changes in linguistic sentiment on other social media platforms where alt-right supporters are active, such as 4Chan and Gab. It may also be of interest to measure concepts other than sentiment and video frequencies, such as hate speech and abusive language, in response to the Charlottesville rally and perhaps other events of interest. Although it is beyond the scope of the current paper, a follow-up study of the specific contexts in which certain sentiment scores are observed may be highly interesting. For example, what exactly is being said about ‘black people’ that leads to a negative trend in the progressive group post-Charlottesville?

VIII. Conclusion

Following the violent rally in Charlottesville, the alt-right received significant attention in the media and public discourse. As a result, we expected to see differences in social identity performance on part of the alt-right movement, which was measured through examining language use. Contrasting a unique dataset of YouTube video transcripts from alternative, right-leaning channels to progressive, left-leaning channels, the present investigation observed differences in temporal trends for the sentiment surrounding some frequent n-grams both within and between the alternative and progressive groups for the different time windows. Results potentially reflect political sentiment after the rally, as well as differences in political sentiment between the two groups more generally.

* Similar to https://mediabiasfactcheck.com/ and https://www.allsides.com/media-bias/media-bias-ratings but for YouTube channels
