Twitter language samples reflect collective emotional responses following political leaders' rhetoric during the pandemic across four countries

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Key words: COVID-19, Twitter, political leaders, socioaffective dynmics, collective emotions

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A functioning society is woven from the fabric of interpersonal dynamics, broadly defined. These interpersonal processes happen in all areas of social life, some more directed and conscious than others. During collectively experienced stressors, such as wars, pandemics, or natural disasters, people often feel a strong urge to share their feelings as a means to regulate their own and others' emotions (Rimé, 2007) – a process known as interpersonal emotion regulation (Horn & Maercker, 2016). Interpersonal emotion regulation can happen in close contact, face-to-face, or in a larger context and through text on social media (Goldenberg & Gross, 2020; Kramer et al., 2014; Rimé, 2020). This social sharing can also result in widespread synchronization of emotion – also referred to as emotional contagion (Rimé, 2020), or coregulation (Butler & Randall, 2012).

The COVID-19 pandemic has been a collectively distressing event, whose considerable length and global impact provides a rare scenario in recent history wherein socioaffective processes are able to be explored and better understood at a global scale (Masiero et al., 2020). Throughout the pandemic, the public has depended extensively on political leaders for guidance, safety, and action. The regulatory measures implemented by political leaders have had a strong impact on wellbeing and mental health, as was shown in studies finding increasing rates of psychological distress during the pandemic (Pierce et al., 2020). The approaches of political leaders around the world displayed a wide range from dangerous denials and spreading misinformation (Dyer, 2020) to smart and practical strategies that clearly prioritized public safety (Varghese & Xu, 2020). However, little is currently known about the direct socioaffective dynamics between political leaders and the public. Understanding how government messaging is associated with the collective wellbeing of society is critical to understand the human condition and will help inform government policy, decision-making, and action (Jordan, 2022). The current study aimed to investigate how government leadership and tactics can directly impact people's resilience and wellbeing. The relevance of these dynamics goes way beyond the COVID-19 pandemic. Even though the decisions of political leaders always affect the people living in their country, a crisis situation such as the COVID-19 pandemic makes this fact more explicit and measurable since decisions of political leaders, such as nation-wide lockdowns, quickly changed the daily lives of people in their respective countries. This also led to a higher more attention to public statements than usual. As an example, a public TV statement by Angela Merkel was watched by 25 million people (https://www.tagesspiegel.de/gesellschaft/medien/25-millionen-zuschauer-sehen-ansprache-der-bundeskanzlerin-8152087.html). The COVID-19 pandemic gives us an opportunity to quantify processes between the collective public and political leaders and learn more about these socioaffective dynamics.

Quantifying Socio-Psychological Processes via Social Media

As introduced above, collectively experienced emotional dynamics are reflected in social media language and can be measured through text analysis (Brummette & Fussell Sisco, 2015; Garcia et al., 2021; Pellert et al., 2020). Besides these expressions of emotional experiences, social media language further provides indicators of the collective focus reflecting either self-references or social references to the community (Ashokkumar & Pennebaker, 2021; Cohn et al., 2004; Garcia & Rimé, 2019). Researchers have expressed the importance of monitoring social media in order to evaluate psychological processes during the pandemic, as it can give insight into public concerns and attitudes and how these change (Cheng et al., 2021; Hanschmidt & Kersting, 2021). Social media language thus gives us valuable insight into collective experiences and wellbeing, and allows us to measure these at scale and in real-time (Barbieri et al., 2020; Garcia et al., 2021; Jordan, 2022). Previous research has found that collective emotions during the pandemic showed different trajectories as compared to pre-pandemic studies (Pellert et al., 2020) and persisted for much longer durations (Ashokkumar & Pennebaker, 2021). Collective coping processes do not show a typical recovery to baseline, as has been found after more short-term collective experienced distress, such as natural disasters or terrorist attacks (Garcia et al., 2021). This shows us how in longer lasting collective experiences and crises, there must be socioaffective processes at play, influencing these collective emotions and coping mechanisms.

Natural language processing tools enable us to reliably investigate collective socioaffective processes reflected in social media and public language with well-established, extensively validated methods (Schwartz et al., 2016; Seabrook et al., 2018). We can employ natural language processing tools to quantify political leader messaging, as has been done in studies analyzing public speeches by political leaders, including debates, campaigns, (Conway et al., 2012; Jordan et al., 2018), and crisis communications (Pennebaker & Lay, 2002), as well as collective emotions expressed in social media language (Ashokkumar & Pennebaker, 2021; Garcia et al., 2021; Pellert et al., 2020). Previous research has looked at each of these variable groups individually and in association with different covariates, but, to our knowledge, never at the bidirectional social psychological dynamics between political leaders and collective emotions directly.

Generally, analytical language indicates more complex, abstract-dynamic thinking. This was first found in college admissions essays, where higher analytical language predicted more academic success (Pennebaker et al., 2014). Consequently, political leaders might convey more competence with this linguistic style. Conveying competence has been of great importance during the pandemic in order for people to trust political leaders (Purdue, 2001). Accordingly, it has been found that political leaders who speak in a more analytical style during their campaign show more electoral success (Conway et al., 2012) but this is simultaneously associated with appearing more distant (Jordan et al., 2018). Expressing negative emotions adequately represents the demanding and severe quality of the crisis situation during the pandemic. A German survey revealed that the majority of participants preferred communication of admitted uncertainty over conveying a false sense of control concerning the COVID-19 pandemic, since such communication would reflect a realistic and adequate idea of the situation (Wegwarth et al., 2020). In contrast to this, governments have often denied the gravity of the situation during previous pandemics by expressing more positivity (Barry, 2004), and some leaders did so during the COVID-19 pandemic as well (Falkenbach & Greer, 2020). Most likely, they were hoping to make a calm impression and keep up positive emotions. There is evidence showing emotional contagion and synchronization also happens within leadership processes, although this was only showed in the work context (Johnson, 2008). An immediate language style is defined as being more concrete, personal, present focused, involved, and experiential, and has been derived in early studies of psychological factors indicated by LIWC categories (Pennebaker & King, 1999). In interviews concerning attachment style, immediacy has been found to be associated with emotional and experiential involvement in a topic (Borelli et al., 2013). Consequently, political leaders with a more immediate language style appear more dynamic and informal (Ahmadian et al., 2017). For these reasons, with a more immediate language style, political leaders are likely to appear more emotionally involved with and closer to the public. During times of crisis, both political leaders and the general population have been found to express more focus on the community and display more references to social connections, measured by more references of first person plural pronouns (e.g, "we", Garcia et al., 2021). We define communal focus as framing an experience or a problem as shared issue (our problem) rather than individual, separate one – mine or yours or theirs. This implies a more communal view on problems at hand and has been associated with cooperative coping strategies (Rohrbaugh et al., 2008). This notion of We-ness is indicated by the use of "we"-words, as has been shown in couples research (Karan et al., 2019) and with people with lower attachment avoidance, that is, more closeness to others (Dunlop et al., 2020), but also in studies focusing on collective processes on the macro-level, for example, after terrorist attacks (Garcia & Rimé, 2019) or tragedies affecting the community (Stone & Pennebaker, 2002). Previous findings show that political leader language is associated with electoral success (Conway et al., 2012), that both political leader language and social media focus more on community during crises (Garcia et al., 2021; Pennebaker & Lay, 2002), and that emotional contagion happens between leaders and the general population (Johnson, 2008). These findings support the assumption that political leader communication and collective affective dynamics are connected with each other. Our study was informed by these findings and was based on a conceptual assumption of a coregulatory process between political leaders and collective emotions expressed on Twitter. It aimed to investigate whether the way political leaders speak with their people covaried with expression of collective emotions over time during the first phase of the COVID 19-pandemic

The Current Research

In this study, we aimed to investigate whether political leader language in public statements during the beginning of the pandemic was able to predict changes in collective emotions across time. We tested two main hypotheses against each other. In our first research inquiry, we assumed that more negative, analytical, and less emotionally involved (i.e., immediate) language of political leaders would predict less negative collective trajectories. Because the coronavirus realistically represents a large threat to many people, high levels of negative emotion can show the public that the situation is being taken seriously (Wegwarth et al., 2020), as opposed to conveying a message of ”everything is all right” when it is not. Analytical language should convey a sense of competence and having the situation under control (Conway et al., 2012; Pennebaker et al., 2014). We call this the message adequacy hypothesis, as it is adequate to recognize the severity of the situation expressed in negative emotions, but also try to convey competence during such a crisis.

The second hypothesis followed the opposite line of argumentation. Here, more positive and emotionally involved language of political leaders was supposed to predict positive changes in emotional responses of the general public. The assumption here was that political leaders being high in positivity and being more immediate (Borelli et al., 2013; Mehl, 2012) would elicit emotional contagion of positive collective emotions (Goldenberg & Gross, 2020; Rimé, 2020). In contrast, an expression of negativity would rather provoke an up-rocking of collective negative emotions through processes of emotional contagion. We named this rationale the emotional contagion hypothesis.

We defined a separate hypothesis around the communal focus of political leaders. We presumed that higher levels of communal focus, measured through the relative count of we-words, in political leader speech, would trigger a higher communal focus in public language as well (Garcia & Rimé, 2019; Pennebaker & Lay, 2002), indicating more solidarity within the general public. Further, we hypothesized that this would also have a positive impact on the public's emotional state, as it conveys a message of solidarity (Garcia & Rimé, 2019). In other words, a focus on communality and solidarity by political leaders would provide a resource for public resilience and soothe negative responses.

We aimed at investigating these hypotheses by exploring the relation between language markers of the speeches and press conferences concerning the COVID-19 pandemic by Donald Trump, Boris Johnson, Angela Merkel, and the Swiss Federal Council (SFC) – which are all the highest executive powers of the respective countries - and the collective emotions expressed on Twitter in their respective nations (USA, UK, Germany, and Switzerland). The SFC, though being a council, is the highest executive power of Switzerland with similar functions as a president, prime minister, or chancellor, just that the power is shared by the seven council members collectively. For more details on the structure and functioning of the SFC, please consult the Supplementary Material.

We focused on the time period between February 27th and August 31st 2020 as the beginning of the pandemic. During the beginning of the pandemic, the countries' situations were relatively similar, and thus, more comparable. We chose these four countries because they are relatively similar in terms of culture and values, considering Hofstede's culture dimensions (https://www.hofstede-insights.com/; Kumar, 2021) and the WEIRD (western, educated, industrialized, rich and democratic) perspective. As we were interested in basic processes of coregulation on the macro-level and we had no specific hypothesis how these processes would be different across countries and leaders, we chose the strategy to only report those associations that remained across countries beyond all the obvious differences at hand. Collective emotions, as introduced above, are expressed and shared on Twitter. In contrast to cross-sectional survey data which captures only one time point, Twitter easily allows for nearly real time daily measurements of real-world behavior (Brummette & Fussell Sisco, 2015; Garcia & Rimé, 2019; Pellert et al., 2020). The research question, analysis plan, and hypotheses were preregistered with the title 'The Language of COVID preregistration' at https://osf.io/wqz84/?view_only=ac65afb7e2604de7a6834cc39a7dee3c. The preregistration involved additional research questions, analysis, and hypotheses going beyond the current study that will not be addressed, as they are beyond the scope of this article. We only considered Research Question 1 of the preregistration. Table S1 in the Supplementary Material shows an overview on adjustments between what was planned in the preregistration and what we implemented in the current study.

Method

Data

Daily language data was sampled from people living in the USA, UK, Germany, and Switzerland via posts made on Twitter by users living in each country. Data was harvested from the Twitter Streaming API in a continuous manner from February 27th to August 31st 2020. We decided to focus on this time period as it was the beginning of the pandemic in which the countries were still in relatively similar situations, whereas later on, they developed in different directions (see https://ourworldindata.org/coronavirus for detailed descriptions of the COVID-19 situations per country). Tweets were collected in a multistage process. First, a custom application "listened" for geolocated tweets that originated from any one of the four countries under study. The aim of the study was to detect possible country-specific association between the political leaders and responses on Twitter in the respective country. Thus, it was of vital importance to be certain of the location of the tweets in order to detect these country-specific effects. The sampling code first randomly selected one of the four nations, then sampled the timeline of the first user provided by the Twitter Streaming API who was tweeting within that nation. This was done to ensure that our sample included active Twitter users rather than users with other, more biased selection criteria. Put another way, our sampling procedure was to simply rely on the randomness of Twitter's API for returning a random, recently active user in one of the four nations under study. Then, all available tweets for a randomly-sampled user were collected, going back as far as their 3,200 most recent posts. In order to model psychological changes over time, it is necessary to capture within-person changes over time to focus on individual changes within persons as they feed in the collective changes we were interested in. Originally, we wanted to model them within a multilevel framework (see the preregistration) to be even more precise in disentangling individual and collective trajectories. Following broadband data collection, we retained only those users whose tweets included at least one COVID-19 related hashtag, building upon lists used in previous work (Chen et al., 2020, a complete list of hashtags used in the current study is presented in the Supplementary Materials). In order to identify relevant hashtags in Germany and Switzerland, we expanded the original list by looking at the most prevalent hashtags from all tweets in our sample that were made only in the German language. Note that the German speaking population makes up the largest part of the Swiss population (Bundesamt für StatistikBFS, 2021). Users were excluded if they had fewer than a total of 50 geolocated tweets in their timeline, which would preclude our ability to confidently establish their permanent location, and additionally, if fewer than 75% of their geolocated tweets originated from one of the four countries from which we intended to sample. This procedure helped to exclude, for example, a person whose data was captured as a result of a single geolocated tweet made during a layover in Switzerland. Within each nation, only tweets made in the primary language of the country were retained (i.e., English for the USA and UK, German for Switzerland and Germany). Finally, tweets were cleaned using standard preprocessing procedures (e.g., the removal of URLs, usernames, etc.) and aggregated by user, by day. This was done because we were interested in one daily value of our variables per user per day as opposed to individual values of specific tweets. All collected tweets were publicly accessible (Stevens et al., 2015), and data usage adhered to Twitter's Terms of Service and Developer's Agreement and Policy.

We collected transcripts of all speeches and press conferences concerning the COVID-19 pandemic by Donald Trump, Boris Johnson, Angela Merkel, and the SFC during the same time period. During his press conferences, Boris Johnson did not answer questions. Consequently, we retained only the language of the other political leaders delivered prior to interaction with audience members to prevent the potential confound of format differences. For Trump, Johnson, and Merkel, the transcripts were all publicly available online. For the SFC, only videos were publicly available on YouTube. These press conferences were manually transcribed. Consistent with our analytic strategy for tweets, only language data in the dominant language of each nation was retained.

Psychological Measures

All transcripts and tweets were analyzed with LIWC2015 (Pennebaker et al., 2015) and DE-LIWC2015 (Meier et al., 2019). LIWC operates by categorizing words within a text across 89 different psychologically significant categories. The resulting values are the percentages of these words in respect to the whole text. LIWC has been explicitly validated in both German (Meier et al., 2019) and English (Pennebaker et al., 2015). Also, the comparability of both these dictionaries has been empirically tested (Meier et al., 2019), which is another reason why we focused on these countries and languages in this study.

For the collective responses of interest on Twitter, we considered following LIWC categories; positive emotion, sadness, anger, anxiety, I-talk, and we-words. For the leader transcripts, we included the positive emotion, negative emotion, and we-words categories from LIWC, and the composite scores for analytical thinking and immediacy. Table 1 shows paraphrased example sentences for each category except for the composite scores (analytic and immediacy), because those are harder to pinpoint in a single sentence.

Emotional expression is measured by counting positive (e.g., "love," "nice," "happy") and/or negative (e.g., "hurt," "nasty," "ugly") emotion words (Tausczik & Pennebaker, 2010). LIWC has specific categories of anger, sadness, and anxiety as subcategories of negative emotions. I-talk is calculated in LIWC as the relative frequency of first-person singular pronouns (i.e., "I," "me," and "my"). High values in I-talk are indicative of excessive self-focus, which is related to negative emotionality and depression (Berry-Blunt et al., 2021; Tackman et al., 2019). For these reasons, I-talk was added in the analysis as an indicator of collective distress. We measured communal focus by first-person plural pronouns (we-words, Pennebaker & Lay, 2002).

The analytical language score in LIWC is derived from so-called function words, which are supposed to reveal how a person thinks as opposed to what they are thinking. Analytical language is indicative of a more dynamic thinking style and is measured by more frequent use of articles and prepositions (Pennebaker et al., 2014). Specifically, the composite score of analytical thinking is calculated with the following formula: 30 + articles + prepositions – personal pronouns – impersonal pronouns – auxiliary verbs – conjunctions – adverbs – negations. This composite score is automatically calculated in LIWC and included in the output.

Fewer articles, more personal pronouns (I-talk) and more discrepancy words (e.g., "would," "should") indicate more immediate language (Pennebaker & King, 1999), which is indicative of more emotional involvement in a topic (Cohn et al., 2004). Immediacy is the only variable in the current study that was not available as a predefined category in LIWC and had to be manually computed. Immediacy was computed by subtracting z-standardized values of articles from I-talk and adding discrepancies and present tense words (I-talk - articles + discrepancy + present tense, Mehl, 2012). Usually, words longer than six letters are also considered in the immediacy score, but because six letter words are generally more frequent in

Table 1. *Paraphrased examples of emotional and social expressions*

Variable	**Example sentence**
Twitter I-talk	#COVID19 I'm not in quarantine, I'm in safety. I'm not being locked up, I'm being protected. I'm not lonely, I have this community.
Twitter positive emotion	fearless, brave, courageous, unafraid yeah – this is the medical staff … #COVID2019
Twitter anxiety	GOOD JOB WITH ALL THE PANIC #Covid_19 #Covid19 #panicshopping #panicbuying #StayAtHome
Twitter sadness	it doesn't hurt to remain at home. however, losing your loved ones does. #NightMention #StayAtHome
Twitter we	We all need to do what we can. #StayHome
Leader positive emotion	But I just want to thank everybody at NIH and all of the great scientists and doctors and everything. I know you're working around the clock. I know you've made some great finds already, and that's — really, it makes us feel very good. (Donald Trump, transcript retrieved from https://www.whitehouse.gov/briefing-room/)
Leader negative emotion	The coronavirus is the biggest threat this country has faced for decades. (Boris Johnson, transcript retrieved from https://www.gov.uk/search/news-and-communications)
Leader we	But we are also working for the future. That is why Germany gave itself the motto: "Together. Make Europe strong again". (Angela Merkel, transcript retrieved from https://www.bundesregierung.de/breg-de/aktuelles/pressekonferenzen)

Note. These Twitter posts were based on posts from our data set but changed so that they cannot be traced back to any specific users. In bold are the words LIWC would count for the corresponding category. Examples for LIWC categories analytical and immediacy are not displayed since these categories are composite scores calculated by multiple categories. Anger is not displayed as the language used in these posts was deemed inappropriate.

German and the inclusion of this category makes the immediacy score less reliable across languages (Meier et al., 2019), we decided not to consider it in both languages.

Data Pre-Processing

After the LIWC analysis, the daily aggregated tweets – which gave one value per variable per day – were excluded from further analysis if the word count of that day was less than ten. Other than the word count, we did not selectively omit any data. 11,314 posts were excluded in the USA, 13,881 in the UK, 3,859 in Germany, and 441 in Switzerland. This resulted in a total of 296,238 Twitter posts, out of which 129,012 Tweets originated in the USA, 127,487 in the UK, 36,266 in Germany, and 3,473 in Switzerland. The tweets stemmed from 33,842 unique users, 12,393 from the USA, 16,634 from the UK, 4,260 from Germany, and 555 from Switzerland. Figure S1 in the Supplementary Material shows word clouds of the Twitter dataset per country, Table S2 in the Supplementary Material shows the most frequent words of the Twitter dataset per country. To compute a daily score of collective emotion, the daily mean of each language variable was calculated for each country, in line with previous studies of collective emotions (Ashokkumar & Pennebaker, 2021; Garcia & Rimé, 2019). There were some days when no Swiss tweets concerning the COVID-19 pandemic were posted. On these days, the variables were set as missing.

There were dates on which political leaders spoke more than once a day. For these days, we combined the individual text files and analyzed them as a single text file so that each day of speech had only one value. The political leaders did not speak on every day that was considered in the current study. Donald Trump spoke on 62 days, Boris Johnson on 21, Angela Merkel on 25, and the SFC on 23. The total word count was 161559 for Trump, 25183 for Boris Johnson, for 22802 Angela Merkel, and 33234 for the SFC. The values of the leaders' language markers were held constant between dates of speeches so that every day had a value. The assumption here was that the communication style would not have an effect only on that day or the next but would stay until they communicated once again. This resulted in a data set with one daily value for each Twitter variable and each leader language variable for each country, structured in a long format with language variables organized by country with each day of the study period representing one line.

Analysis

In order to focus on robust dynamics within countries and partial out country differences, we first z-standardized all variables within countries across all days. Then, we computed a correlation matrix to check for contemporary associations between leader speech and Twitter variables. Next, one-day-lagged variables were created. This means that for each variable, the value of the same variable the day before was put into a new variable on the same row.

To check the robustness and temporal unfolding across one day (lag 1) of the contemporary associations found in the correlation matrix, we next conducted a longitudinal analysis between those variables that showed a significant correlation. We chose the lag of one day on the basis of earlier studies suggesting a short-term association of collectively experienced events with collective emotional expression (Garcia & Rimé, 2019; Metzler et al., 2022; Pellert et al., 2022). What is more, leader speeches were held constant across several days, further contributing to the expectation of day-to-day associations between the variables.

We conducted a time series analysis using Bayesian estimators in MPlus version 8 (Muthén & Muthén, 2017). We applied cross-lagged models for continuous variables, which belong to the family of vector auto-regressive (VAR) models (Hamilton, 1994), in order to detect association between time series'. Please note that given the small N of the four countries, we followed the general recommendations to not apply a multilevel model (Bryan & Jenkins, 2016). Adding enough countries to conduct a multilevel analysis would have complicated the analysis due to unavoidable large cultural and linguistic differences. With our approach of *z*-standardizing our variables per country and eliminating country-level differences, we aimed at investigating dynamic associations across countries that are robust above and beyond absolute level differences. We built our model as follows: We regressed all Twitter variables on themselves at the previous time point (lag 1, auto-regression) and on the previous time point of those political leader variables with which they had shown a significant, contemporary correlation. We did the same for political leader variables, respectively, in order to control for possible associations in the opposite directions and explore the relation between political leader language and collective emotions in both directions.

Furthermore, as a control variable, COVID-19 daily infection rates were z-standardized per country and included in the analysis. Country was further controlled for by inserting dummy codes for the UK, Germany, and Switzerland, with the USA as reference category. To additionally control for impactful events that were specific to individual countries during the investigated time period, we added a dummy code in the UK before (0) and after (1) Boris Johnson's infection with COVID-19 (held at zero in all other countries). In the USA, we added a dummy code before (0) and after (1) the killing of George Floyd by US police officers which sparked protests against police brutality and the beginning of the Black Lives Matter movement (held at zero in all other countries). These dummy codes were added as control variables to control for effects which were specific to these events, and, in turn, to these countries since no comparable events happened in the other countries.

All regressions were combined into one model and all variables were allowed to covary, and therefore, were controlled for. Significance was defined by a p value of $< .05$ and a confidence interval (CI) that did not contain zero. p value equivalents for Bayesian analyses were computed by averaging over the distribution of p values and they describe the probability, given the present data, that a future observation is more extreme than the data (Gelman, 2005). As an additional analysis, we computed the same model for each country separately as well.

We have adjusted the data analysis strategy since the preregistration. We had originally planned to consider each individual Twitter user in a latent growth analysis. The structure of the Twitter data with each individual user included a very large number of missing values, as not every user tweeted about the pandemic every day. What is more, analysis with this data would have resulted in an overestimation of those users who did post nearly every day (so-called super users) and would not have represented collective emotions. Thus, we decided to aggregate all individual tweet values to collective daily means, which is also in line with previous research on collective emotions (Ashokkumar & Pennebaker, 2021; Garcia & Rimé, 2019). This data structure called for different analysis since latent growth models (which were preregistered) were not feasible with such data.

Results

Table 2 shows the correlations. Table 3 shows the results of the VAR(1) conducted on all significant correlations between political leaders and Twitter variables.

The time series' analysis showed, analytical language style of political leaders statistically significantly and positively predicted positive emotion, $\beta = .08$; $p = .02$; 95% CI = (.00; .16), and we-words, $\beta = .07$; $p = .02$; 95% CI = (.00; .17), on Twitter one day later, over and above all control variables. Negative emotion of political leaders statistically significantly positively predicted we-words, $\beta = .08$; $p = .01$; 95% CI = (.02; .18), on Twitter one day later, over and above all control variables. We-words of political leader statistically significantly positively predicted positive emotion, $\beta = .09$; $p = .00$; 95% CI = (.02; .16), and negatively predicted anxiety, $\beta = -.10$; $p = .00$; 95% CI = (-.16; -.04), and sadness, $\beta = -.07$; $p = .01$; 95% CI = (-.15; -.01), on Twitter one day later, over and above all control variables. The posterior predictive p value of the VAR(1) model across all countries rendered .08 and the 95% CI for the difference between observed and replicated χ^2 was [-27.60; 128.07], indicating adequate fit (Muthen & Asparouhov, 2012). An adequate model fit was defined as a posterior predictive p value of >.05 and a 95% CI containing 0, as suggested by Muthen and Asparouhov (2012). Figure 1 shows the trajectories of we-words of political leaders and the Twitter variables it significantly predicted over the selected time period. Figures 2 and 3 show the same for negative emotion in leader language and analytical leader language.

These results more closely support our message adequacy hypothesis than the emotional contagion hypothesis, as the public showed more positive emotions, fewer negative emotions, and more social connectedness following days where leaders spoke more analytically or more negatively. Furthermore, the results support some of the effects we expected around the we-words of political leaders, as the public expressed more positive emotion and less anxiety as well as sadness following the days where leaders expressed more communal focus.

All variables, except for anger on Twitter, showed significant autoregression. These were generally stronger in the leader variables as compared to the Twitter variables. The strong autocorrelation for the leaders are not surprising as people tend to speak in a similar style across time (Boyd & Pennebaker, 2017). Here, the values only came from one individual (or council) as opposed to the Twitter values, which were a measure of the collective based on many individual people. All control variables showed some predictive value on most of the Twitter variables (see Supplementary Material Table S3). We found effects of the country dummy codes regarding collective emotional responses on Twitter which reflect differences in changes of collective emotions between countries while controlling for level differences (as the variables were z-standardized per country). We observed no such effects of country dummy codes on political leader language use over time.

The models computed per country showed different results than the overall model and in two countries, the model fit was not adequate (posterior predictive p value < .05 (Muthen & Asparouhov, 2012). The results of these models can be found in the Supplementary Material Tables S4-S7. The separate models of Germany and the UK showed satisfactory model fit. The results in the UK resembled the associations of analytical and we-words of leaders found in the overall model. In Germany, these effects were not found. Furthermore, we found some effects of Twitter variables on political leader speech in both Germany and UK.

In order to better understand our results, we additionally decided to take a closer look at the data descriptively. Figure 4 shows a barplot of the means and

Table 2. *Correlations*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk	1										
Twitter positive emotion	.145**	1									
Twitter anxiety	.079*	-.321**	1								
Twitter anger	.062	-.185**	.113**	1							
Twitter sadness	-.030	-0.013	-.042	.094*	1						
Twitter we	.069	.114**	-.106**	-.023	.023	1					
Leader positive emotion	-.050	.124**	-.222**	-.023	.102**	.044	1				
Leader negative emotion	.045	.061	-.100**	.044	-.092*	.139**	-.236**	1			
Leader we	-.011	.194**	-.226**	-.124**	-.104**	0.045	.137**	.162**	1		
Leader analytic	.045	.216**	-.254**	-.106**	-.079*	.116**	.190**	.297**	.294**	1	
Leader immediacy	.109**	.031	.083*	.049	.017	-.003	.075*	-.095**	.002	-.397**	1

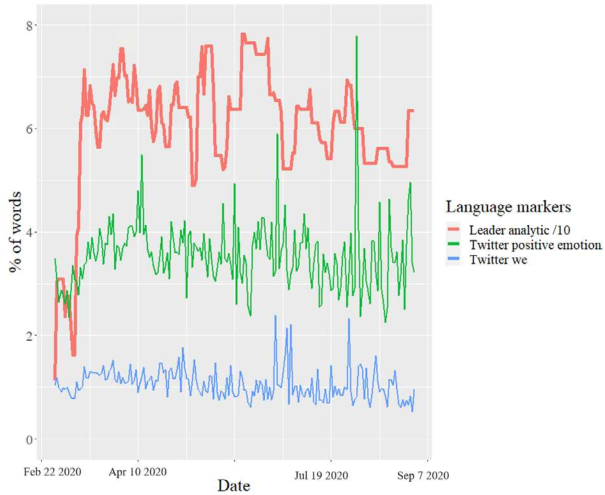
Note. *** $p < .001$; ** $p < .01$; * $p < .05$

SDs of the language markers of political leaders. What we found most striking was that Donald Trump and Boris Johnson showed higher levels of negative emotions compared to the other two political leaders. We did not test these differences for statistical significance. Nonetheless, Trump and Johnson were publicly accused of not taking the pandemic seriously enough (Dyer, 2020; Falkenbach & Greer, 2020). This is why this raises serious doubts if our previous interpretation of higher values of negative emotion as representing taking the situation seriously and recognizing the gravity of the situation is correct.

Discussion

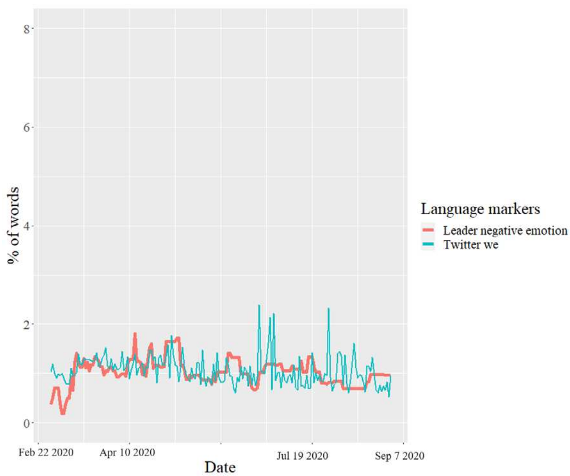
The goal of the current study was to investigate whether communication by political leaders would be associated with changes in collective emotional responses during the COVID-19 pandemic. The pandemic, as a worldwide, long-term stressor, provides a unique opportunity to study the role of political leaders in general processes of interpersonal emotion regulation concerning the same stressor across different countries. Our findings support the idea that in a collective crisis, political leaders who acknowledge the negative nature of the situation, convey their message in a competent way, and focus on solidarity

Figure 1. *Political leader analytical language, Twitter we-words, and positive emotion across time*



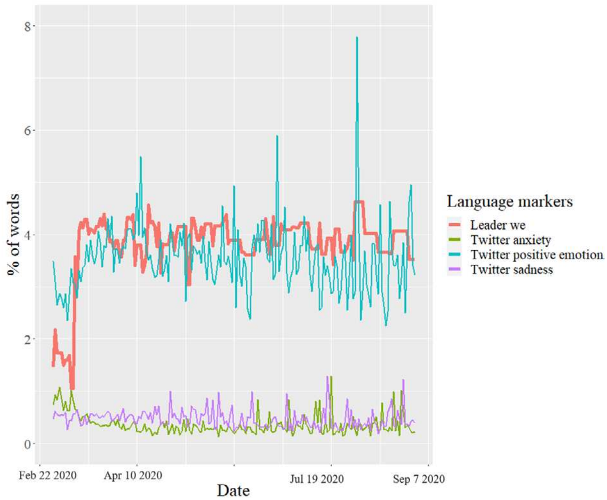
Note. The x-axis represents time in days. All variables are reported in daily means. Political leader language represents the mean of all political leaders. It was divided by 10 in order to scale it more closely to the Twitter variables. Twitter variables represent the mean of all countries. Political leader analytical language was able to significantly predict more we and positive emotion Twitter one day later.

Figure 2. *Political leader negative emotion and Twitter we-words across time*



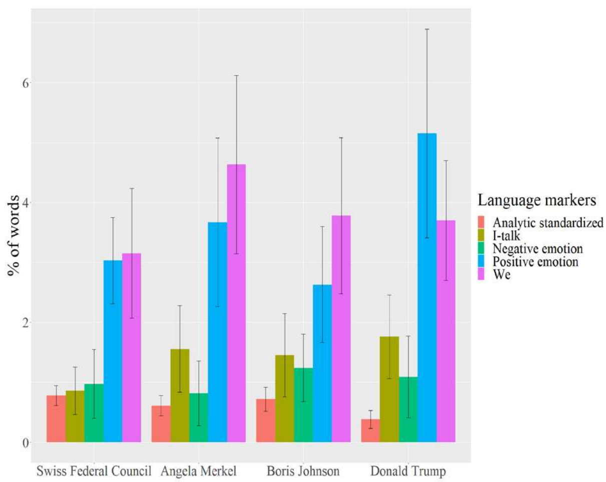
Note. The x-axis represents time in days. All variables are reported in daily means. Political leader language represents the mean of all political leaders. Twitter variables represent the mean of all countries. Political leader negative emotion was able to significantly predict more we on Twitter one day later.

Figure 3. *Political leader we-words and Twitter positive emotion, anxiety, and sadness across time*



Note. The x-axis represents time in days. All variables are reported in daily means. Political leader language represents the mean of all political leaders. Twitter variables represent the mean of all countries. Political leader we was able to significantly predict more positive emotion and less anxiety and sadness on Twitter one day later.

Figure 4. *Mean language markers of each political leader*



Note. Bars represent the mean language markers over across the analyzed time period (February to August 2020), error bars represent +/- 1 SD. We displayed I-talk here as an indicator of immediacy.

Table 3. *VAR(1) model: Time series analysis between leadership language use and collective emotional responses: Tested temporal unfolding of contemporary correlations*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk t-1	*.23*** [.18;.30]*										.02 [-.02;.05]
Twitter positive emotion t-1		*.17*** [.11;.23]*					.01 [-.02;.05]		.04 [-.01;.08]	.04 [-.00;.07]	
Twitter anxiety t-1			*.26*** [.20;.33]*				.01 [-.03;.06]	.00 [-.03;.05]	-.03 [-.08;.02]	.01 [-.03;.05]	.02 [-.02;.07]
Twitter anger t-1				*.05 [-.02;.12]*					-.03 [-.08;.01]	.00 [-.03;.03]	
Twitter sadness t-1					*.12*** [.03;.20]*		.00 [-.04;.04]	-.00 [-.04;.02]	.01 [-.04;.06]	-.01 [-.04;.02]	
Twitter we t-1						*.16*** [.09;.23]*		.01 [-.02;.05]		.02 [-.01;.04]	
Leader positive emotion t-1		.04 [-.02;.12]	-.07 [-.14;.00]		.05 [-.03;.12]		*.83*** [.81;.86]*				
Leader negative emotion t-1			-.01 [-.08;.04]		-.07 [-.13;.02]	**.08*** [.02;.18]**		*.86*** [.84;.88]*			
Leader we t-1		**.09** [.02;.16]**	-.10*** [-.16;-.04]	-.05 [-.13;.02]	**-.07** [-.16;-.01]**				*.80*** [.76;.81]*		
Leader analytic t-1		**.08** [.00;.16]**	-.07 [-.14;.00]	.04 [-.03;.10]	-.01 [-.08;.06]	**.07*** [.00;.17]**				*.83*** [.81;.86]*	
Leader immediacy t-1	.04 [-.02;.12]		.05 [-.04;.11]								*.82*** [.80;.84]*
Explained Variance: R^2	.21*** [.16;.26]	.17*** [.13;.23]	.27*** [.22;.31]	.11*** [.08;.15]	.10*** [.06;.14]	.07*** [.04;.11]	.72*** [.69;.75]	.76*** [.73;.78]	.68*** [.64;.71]	.73*** [.71;.75]	.69*** [.66;.71]

Note. Table shows standardized regression coefficients of the VAR (1) model. Only significant contemporary correlations (see Table 1) were tested for associations across time (see analysis section for detailed description). Significant effects in bold. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. *p* values are computed by averaging distribution of *p* values (Gelman, 2005). 95% CI in square brackets. Diagonal line represents autoregression (lag1) in italics. Model included associations in opposite directions, with leader variables as dependent and Twitter variables t-1 as independent variables (see Table S2 in the Supplementary Material). All dependent variables were further controlled for country (dummy codes for UK, Germany, and Switzerland), infection rates, Boris Johnsons infection in the UK, and George Floyd's killing in the USA (see Table S1 in the Supplementary Material). Posterior-predictive-*p* value of entire model = .083, 95% CI for difference between observed and replicated X^2 = [-27.60; 128.07]. Diagonal line represents autoregression (lag1) in italics.

seem to predict more adaptive processes in the emotional response of the public. In contrast to other perspectives underlining the possible effects of social contagion of emotions between people in societies (Kramer et al., 2014; Rimé, 2020), processes of emotional contagion between political leaders and collective emotions did not prove to be dominant in this situation.

We found that negative emotions expressed by political leaders as well as an analytical language style predicted a communal focus on Twitter. Furthermore, analytical language style of political leaders showed a positive association with positive collective emotions the next day. We had hypothesized analytical and negative language to predict less negative emotion in our Twitter sample. Our results partially support our message adequacy hypothesis. This shows that conveying competence through the analytical language style is connected to collective resilience and wellbeing. We expected analytical language and negative emotion to be more likely associated with emotional changes than we-words on Twitter. Previous literature has found we-words on Twitter to increase during collective crisis situations and to be indicators of expressed solidarity within a community, as they indicate a focus on the community rather than the individual (Garcia & Rimé, 2019). Our results suggest that talking in an analytical way and expressing negative emotionality during a crisis seems to foster this kind of solidarity within our Twitter sample, measured in communal focus on Twitter. Considering that Trump and Johnson expressed more negative emotions compared to the other political leaders, it is less conclusive what the negative emotional tone in political leader speeches conveyed during the COVID-19 pandemic. First, it is possible that the negative emotions expressed by political leaders were not always directed toward the COVID-19 pandemic but toward other, related topics. Further, it is also imaginable that negative emotions expressed by political leaders – toward any topic - trigger more solidarity within the collective through processes of feeling anxious and wanting to stick together. This interpretation is in contrast with our message adequacy hypothesis. Further context-sensitive research is needed to better understand of the role of negative emotional tone in leader language during crisis. It can be stated that we did not find any contagion of negative emotional tone of leader language reflected in the Twitter responses. Furthermore, the association we found between analytical language and positive collective emotion still supports our message adequacy hypothesis. In sum, more research is needed to fully understand the meanings and socioaffective processes between political leader speeches and the collective. Our research gives first insight that there are measurable dynamic processes happening between political leaders and the collective public.

We found no evidence supporting the emotional contagion hypothesis. Here, we had hypothesized that more immediate and positive language of political leaders would be associated with more positive emotion on Twitter. No synchronization of any language indicator between political leaders and Twitter could be observed. Studies in other contexts of leader–follower relationships have shown people to synchronize their emotions with leaders of a group

(Johnson, 2008). This effect is likely different for such large groups which are not necessarily in direct contact with their leader, such as the societies of the countries considered in this study. Furthermore, people are able to voice their opinions on Twitter (more or less) anonymously, which fosters disclosure. What is more, the specific context of a collective crisis in which people strongly depend on their political leaders to guide them might also explain the lack of this effect. Strategies of not communicating the gravity of the situation, but trying to keep positive emotions up do not seem to have a positive effect on collective wellbeing. Interpersonal socioaffective dynamics occurring between political leaders and collective emotions are likely to go beyond emotional contagion in this context.

As hypothesized, a communal focus of political leaders was further associated with decreases in collective distress and increases in collective wellbeing. In other words, communication of political leaders focusing on community and solidarity might present a further offer of coregulation of collective affective dynamics associated with resilient collective responses.

We did not find the hypothesized effect that we-words of political leaders would have an effect on communal focus or I-talk on Twitter. In fact, none of the leader speech variables seemed to have an effect on collective I-talk. This can be explained by previous findings where I-talk was found to have somewhat of a different function in social media language than in private language. For example, associations with negative emotionality have been found to be weaker in this context (Schwartz et al., 2014) than in other situations (Tackman et al., 2019).

It is possible that political leaders played a stronger role in the dynamics of collective emotional responses during the COVID-19 pandemic than during other collectively experienced events because their decisions and communications repeatedly influenced the daily lives of people. On the other hand, such direct associations between leader speech and collective emotion during collectively experienced events previously have not yet been investigated, and our study gives valuable insight into socioaffective dynamics between the two. Researchers have mainly focused either on collective emotion (Garcia & Rimé, 2019) or political leader speech (Pennebaker & Lay, 2002) individually, or discussed associations descriptively (Jordan et al., 2018). Interpersonal socioaffective dynamics between leaders and collective emotions might also occur during more short-lived collective events. Future studies could research these events retrospectively in terms of political leader – collective emotion associations, since data is likely to still be available. What is more, our Twitter dataset included only tweets concerning the COVID-19 pandemic. Future research could investigate if similar effects can be found generally in collective emotions that are not directed toward the pandemic specifically. Furthermore, further studies should look more into specific processes in different countries. The impactful events we added as dummy codes in the UK and USA showed effects on collective emotional responses.

Since between-country differences were not the focus of this study, they will only be discussed shortly. First of all, leaders of the four countries differed descriptively regarding their language style (see Figure 4). We found different results in our country-specific models (see Tables S3-S6 in the Supplementary Material for details). These results might be due to differences in power between the overall model and the country-specific models. Our goal was to show general effects across all countries, which were best detected by combining the data and calculating a model with the most possible power. Further, we believe that the differing results regarding the associations to the Twitter responses specific to countries imply political leader- and country-specific processes. It is very likely that other countries show even more diverse effects (Metzler et al., 2022) since the countries included in this study were all similar in culture and values that have been found to be connected to COVID-19 morbidity and mortality (Kumar, 2021). Future research could investigate other countries with different cultural values. Furthermore, in the country-specific models, we found some effects of lagged public collective emotions on leader speech. In the USA, UK, and Germany, negative emotions such as anxiety and sadness on Twitter were able to predict language variables of the political leaders (see Tables S3-S5 in the Supplementary Material for details). This hints at interpersonal emotion regulation going both ways and that leaders might also react to collective emotions. We did not find any such effects in our general model, which was not designed to investigate country differences but rather to detect overall associations across countries. Further research is warranted to investigate the expected specificities of individual political leaders and their interplay with collective affective dynamics.

Limitations

There are several limitations to this study that should be discussed. First, the effects we found between leader speech and affective dynamics were small. Nonetheless, previous literature has pointed out that these effects are also important to consider (Cortina & Landis, 2009; Götz et al., 2022). Obviously, the real-word indicators used in this study are influenced by a multitude of aspects – so the small effects do not come as a surprise. It is important to note that the indicators of this study are all at scale, as we included a very large number of COVID-related posts on Twitter and all COVID-related public statements of the political leaders. We are aware that if we had not excluded tweets without geolocation, our sample would have been much larger and that we might face selection effects in our Twitter corpus. As explained above, the geolocation was of vital importance for our research question, which is why we decided to exclude any tweets where we could not be sure where they originated from. Moreover, the reported effects are apparent across four countries and are not mere reflections of the severity of the situation, since COVID-19 infection rates were controlled for. Accordingly, one could argue that the observed small effects are robust and open the door for further studies replicating the found associations. What is more, we could detect temporal associations within the lag of one day. However, further research is needed to get a better understanding of the time scale of collective regulation processes.

Even though we tried to investigate regionally overarching coregulatory patterns, there might be limits of generalizability that need to be taken into account. First, the four countries included in analysis were all WEIRD societies. We selected these four countries because they seemed relatively comparable in cultural aspects. Additionally, LIWC is well established in both English and German. What is more, Twitter users are not necessarily representative of the whole population. In the US, Twitter users tend to be younger, have a better education, and higher income than the general population (Hughes & Wojcik, 2019). Importantly, our study did not aim at investigating individual experiences but collective ones. Daily mean levels of Twitter variables have been previously used as a measure for collective experiences (Ashokkumar & Pennebaker, 2021; Garcia & Rimé, 2019). Furthermore, the number of unique users sharing their thoughts and emotions about same topic and contributing to the collective values in our data (N = 33,842) offers access to collective affective dynamics at a different scale as compared to self-reports (Ashokkumar & Pennebaker, 2021; Garcia & Rimé, 2019; Pellert et al., 2020).

Next to LIWC, there are many other natural language processing tools. The LIWC variables have been validated and shown to indicate the psychological variables of interest in the literature (e.g. Pennebaker & King, 1999; Pennebaker & Lay, 2002; Tackman et al., 2019; Tausczik & Pennebaker, 2010), which is why we decided to rely on these measures. Further studies could additionally contribute to a better understanding of linguistic functions in this area by applying other tools, which are not dictionary based approaches, to the dataset used in the current study.

Conclusions

In summary, our results point at interpersonal coregulation between leaders and collective emotions that are not driven by emotional contagion. It appears a community oriented and competent communication of political leaders about the COVID-19 pandemic could help people stay resilient in stressful times. The lack of synchronization is interesting and implies an asymmetrical and distant relationship between political leaders and the Twitter sample. Our data rather suggests that emphasizing the shared nature of an experience and providing a communal perspective during crisis is associated with more positive responses in collective affect. Our results imply that when political leader express negative emotions, it triggers solidarity within the public in collectively experienced crises. Here, further research is needed, as our data could not give a clear picture of what negative emotions of political leaders exactly expresses. We found effects across all countries, but also identified different associations in each country, hinting at country-specific processes. Future work should consider exploring coregulation of emotion between leaders and groups in other countries and contexts (i.e., during other events or with other types of groups) in order to gain more insight into the association between leaders and collective affective dynamics.

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Conflict of Interest Disclosure

All authors declare no conflicts of interest.

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Research Ethics Statement

Ethical approval was not necessary for the current study as it only used publicly available data.

Data Availability Statement

The anonymized, quantified datasets analyzed for this study, as well as a list of the Twitter ID's included in analysis are publicly available on OSF at https://osf.io/a6498/?view_only=246eca197583482ca3713d3b7dec9459. The underlying natural language data used in the current study are not publicly available as per the Twitter EULA. All underlying data may be made available upon request, subject to an appropriate data use agreement.

Authorship Details

Olenka Dworakowski: collection and/or assembly of the data, data analysis and interpretation, writing the article; Ryan L. Boyd: research concept and design, collection and/or assembly of data, critical revision of the article; Tabea Meier: research concept and design, critical revision of the article; Peter Kuppens: data analysis and interpretation, critical revision of the article; Matthias R. Mehl: critical revision of the article; Fridtjof W. Nussbeck: data analysis and interpretation, critical revision of the article; Andrea B. Horn: research concept and design, collection and/or assembly of data, data analysis and interpretation, critical revision of the article, final approval of the article.

References

Ahmadian, S., Azarshahi, S., & Paulhus, D. L. (2017). Explaining Donald Trump via communication style: Grandiosity, informality, and dynamism. *Personality and Individual Differences, 107*, 49–53. https://doi.org/10.1016/j.paid.2016.11.018

Ashokkumar, A., & Pennebaker, J. W. (2021). The social and psychological changes of the first months of COVID-19. *PsyArXiv*. https://doi.org/10.31234/osf.io/a34qp

Barbieri, F., Camacho-Collados, J., Neves, L., & Espinosa-Anke, L. (2020). TweetEval: Unified benchmark and comparative evaluation for Tweet classification (arXiv:2010.12421). *arXiv*. http://arxiv.org/abs/2010.12421

Barry, J. M. (2004). *The great influenza: The epic story of the deadliest plague in history.* Viking Press.

Berry-Blunt, A. K., Holtzman, N. S., Donnellan, M. B., & Mehl, M. R. (2021). The story of "I" tracking: Psychological implications of self-referential language use. *Social and Personality Psychology Compass*. https://doi.org/10.1111/spc3.12647

Borelli, J. L., David, D. H., Rifkin-Graboi, A., Sbarra, D. A., Mehl, M. R., & Mayes, L. C. (2013). Language use in the Adult Attachment Interview: Evidence for attachment-specific emotion regulation. *Personal Relationships, 20*(1), 23–37. https://doi.org/10.1111/j.1475-6811.2012.01394.x

Boyd, R. L., & Pennebaker, J. W. (2017). Language-based personality: A new approach to personality in a digital world. *Current Opinion in Behavioral Sciences, 18*, 63-68. https://doi.org/10.1016/j.cobeha.2017.07.017

Brummette, J., & Fussell Sisco, H. (2015). Using Twitter as a means of coping with emotions and uncontrollable crises. *Public Relations Review, 41*(1), 89–96. https://doi.org/10.1016/j.pubrev.2014.10.009

Bryan, M. L., & Jenkins, S. P. (2016). Multilevel modelling of country effects: A cautionary tale. *European Sociological Review, 32*(1), 3–22. https://doi.org/10.1093/esr/jcv059

Bundesamt für Statistik (BFS). (2021). *Sprachliche Praktiken in der Schweiz—Erste Ergebnisse der Erhebung zur Sprache, Religion und Kultur 2019. Bundesamt Für Statistik (BFS)*.

Butler, E. A., & Randall, A. K. (2012). Emotional coregulation in close relationshiups. *Emotion Review, 5*(2), 202–210. https://doi.org/10.1177/1754073912451630

Chen, E., Lerman, K., & Ferrara, E. (2020). *The First public coronavirus Twitter dataset.* https://arxiv.org/abs/2003.07372

Cheng, I. K., Heyl, J., Lad, N., Facini, G., & Grout, Z. (2021). Evaluation of Twitter data for an emerging crisis: An application to the first wave of COVID-19 in the UK. *Scientific Reports, 11*(1), 19009. https://doi.org/10.1038/s41598-021-98396-9

Cohn, M. A., Mehl, M. R., & Pennebaker, J. W. (2004). Linguistic markers of psychological change surrounding September 11, 2001. *Psychological Science, 15*(10), 687–693. https://doi.org/10.1111/j.0956-7976.2004.00741.x

Conway, L. G., Gornick, L. J., Burfeind, C., Mandella, P., Kuenzli, A., Houck, S. C., & Fullerton, D. T. (2012). Does complex or simple rhetoric win elections? An integrative complexity analysis of U.S. presidential campaigns: Complexity and electoral success in U.S. presidential campaigns. *Political Psychology, 33*(5), 599–618. https://doi.org/10.1111/j.1467-9221.2012.00910.x

Cortina, J. M., & Landis, R. S. (2009). When small effect sizes tell a big story, and when large effect sizes don't. In: C. Lance & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends: Doctrine, verity and fable in the organizational and social sciences* (pp. 287–308). Routledge.

Dunlop, W. L., Karan, A., Wilkinson, D., & Harake, N. (2020). Love in the first degree: Individual differences in first-person pronoun use and adult romantic attachment styles. *Social Psychological and Personality Science, 11*(2), 254-265. https://doi.org/10.1177/1948550619847455

Dyer, O. (2020). Trump claims public health warnings on COVID-19 are a conspiracy against him. *BMJ, m941*. https://doi.org/10.1136/bmj.m941

Falkenbach, M., & Greer, S. L. (2020). Denial and distraction: How the populist radical right responds to COVID-19 comment on "A scoping review of prr parties' influence on welfare policy and its implication for population health in Europe". *International Journal of Health Policy and Management, 1*. https://doi.org/10.34172/ijhpm.2020.141

Garcia, D., Pellert, M., Lasser, J., & Metzler, H. (2021). Social media emotion macroscopes reflect emotional experiences in society at large. *ArXiv:2107.13236 [Cs]*. http://arxiv.org/abs/2107.13236

Garcia, D., & Rimé, B. (2019). Collective emotions and social resilience in the digital traces after a terrorist attack. *Psychological Science, 30*(4), 617–628. https://doi.org/10.1177/0956797619831964

Gelman, A. (2005). Comment: fuzzy and Bayesian p-values and u-values. *Statistical Science, 20*(4). https://doi.org/10.1214/088342305000000368

Goldenberg, A., & Gross, J. J. (2020). Digital emotion contagion. *Trends in Cognitive Sciences, 24*(4), 316–328. https://doi.org/10.1016/j.tics.2020.01.009

Götz, F. M., Gosling, S. D., & Rentfrow, P. J. (2022). Small effects: The indispensable foundation for a cumulative psychological science. *Perspectives on Psychological Science, 17*(1), 205-215. https://doi.org/10.1177/1745691620984483

Hamilton, J. D. (1994). *Time series analysis.* Princeton University Press.

Hanschmidt, F., & Kersting, A. (2021). Emotions in Covid-19 Twitter discourse following the introduction of social contact restrictions in Central Europe. *Journal of Public Health, 14*. https://doi.org/10.1007/s10389-021-01613-y

Horn, A. B., & Maercker, A. (2016). Intra- and interpersonal emotion regulation and adjustment symptoms in couples: The role of co-brooding and co-reappraisal. *BMC Psychology, 4*(1), 51. https://doi.org/10.1186/s40359-016-0159-7

Hughes, A., & Wojcik, S. (2019, August 2). 10 facts about Americans and Twitter. *Pew Research Center.* https://www.pewresearch.org/fact-tank/2019/08/02/10-facts-about-americans-and-twitter/

Johnson, S. K. (2008). I second that emotion: Effects of emotional contagion and affect at work on leader and follower outcomes. *The Leadership Quarterly, 19*(1), 1–19. https://doi.org/10.1016/j.leaqua.2007.12.001

Jordan, K. (2022). Language analysis in political psychology. In: R. L. Boyd & M. Dehghani (Eds.), *Handbook of language analysis in psychology* (pp. 159–172). Guilford Publications.

Jordan, K. N., Pennebaker, J. W., & Ehrig, C. (2018). The 2016 U.S. presidential candidates and how people tweeted about them. *SAGE Open, 8*(3), 215824401879121. https://doi.org/10.1177/2158244018791218

Karan, A., Rosenthal, R., & Robbins, M. L. (2019). Meta-analytic evidence that we-talk predicts relationship and personal functioning in romantic couples. *Journal of Social and Personal Relationships, 36*(9), 2624–2651. https://doi.org/10.1177/0265407518795336

Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences, 111*(24), 8788–8790. https://doi.org/10.1073/pnas.1320040111

Kumar, R. (2021). Impact of societal culture on COVID-19 morbidity and mortality across countries. *Journal of Cross-Cultural Psychology, 52*(7), 643–662. https://doi.org/10.1177/00220221211025100

Masiero, M., Mazzocco, K., Harnois, C., Cropley, M., & Pravettoni, G. (2020). From individual to social trauma: Sources of everyday trauma in Italy, the US and UK during the COVID-19 pandemic. *Journal of Trauma & Dissociation, 21*(5), 513–519. https://doi.org/10.1080/15299732.2020.1787296

Mehl, M. R. (2012). How taking a word for a word can be problematic: Context-dependent linguistic markers of extraversion and neuroticism. *Journal of Methods and Measurement in the Social Sciences, 3*(2), 30–50.

Meier, T., Boyd, R. L., Pennebaker, J. W., Mehl, M. R., Martin, M., Wolf, M., & Horn, A. B. (2019). “LIWC auf Deutsch”: The development, psychometrics, and introduction of DE-LIWC2015. *PsyArXiv*. https://doi.org/10.31234/osf.io/uq8zt

Metzler, H., Rimé, B., Pellert, M., Natale, A. D., & Garcia, D. (2022). Collective Emotions during the COVID-19 outbreak. *Emotion, 23*(3), 844–858. https://doi.org/10.1037/emo0001111

Muthen, B., & Asparouhov, T. (2012). Bayesian SEM: A more flexible representation of substantive theory. *Psychological Methods, 17*(3), 78.

Muthén, L. K., & Muthén, B. O. (2017). *Mplus user's guide* (8th ed.). Muthén & Muthén.

Pellert, M., Lasser, J., Metzler, H., & Garcia, D. (2020). Dashboard of sSentiment in Austrian social media during COVID-19. *Frontiers in Big Data, 3*, 32. https://doi.org/10.3389/fdata.2020.00032

Pellert, M., Metzler, H., Matzenberger, M., & Garcia, D. (2022). Validating daily social media macroscopes of emotions. *Scientific Reports, 12*(1), 11236. https://doi.org/10.1038/s41598-022-14579-y

Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. https://repositories.lib.utexas.edu/handle/2152/31333.

Pennebaker, J. W., Chung, C. K., Frazee, J., Lavergne, G. M., & Beaver, D. I. (2014). When small words foretell academic success: The case of college admissions essays. *PLoS One, 9*(12), e115844. https://doi.org/10.1371/journal.pone.0115844

Pennebaker, J. W., & King, L. A. (1999). Linguistic styles: Language use as an individual difference. *Journal of Personality and Social Psychology, 77*(6), 1296–1312.

Pennebaker, J. W., & Lay, T. C. (2002). Language use and personality during crises: Analyses of mayor Rudolph Giuliani's press conferences. *Journal of Research in Personality, 36*(3), 271–282. https://doi.org/10.1006/jrpe.2002.2349

Pierce, M., Hope, H., Ford, T., Hatch, S., Hotopf, M., John, A., Kontopantelis, E., Webb, R., Wessely, S., McManus, S., & Abel, K. M. (2020). Mental health before and during the COVID-19 pandemic: A longitudinal probability sample survey of the UK population. *The Lancet Psychiatry, 7*(10), 883–892. https://doi.org/10.1016/S2215-0366(20)30308-4

Purdue, D. (2001). Neighbourhood governance: Leadership, trust and social capital. *Urban Studies, 38*(12), 2211–2224. https://doi.org/10.1080/00420980120087135

Rimé, B. (2007). Interpersonal emotion regulation. In: J. J. Gross (Ed.), *Handbook of emotion regulation* (pp. 466–468). The Guilford Press.

Rimé, B. (2020). Collective responses to collective traumas: Synchronization and collective resilience. In: D. Jodelet, J. Vala, & E. Drozda-Senkowska (Eds.), *Societies under threat* (Vol. 3, pp. 201–211). Springer International Publishing.

Rohrbaugh, M. J., Mehl, M. R., Shoham, V., Reilly, E. S., & Ewy, G. A. (2008). Prognostic significance of spouse we talk in couples coping with heart failure. *Journal of Consulting and Clinical Psychology, 76*(5), 781. https://doi.org/10.1037/a0013238

Schwartz, H. A., Eichstaedt, J., Kern, M. L., Park, G., Sap, M., Stillwell, D., Kosinski, M., & Ungar, L. (2014). Towards assessing changes in degree of depression through Facebook. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, 118–125. https://doi.org/10.3115/v1/W14-3214

Schwartz, H. A., Sap, M., Kern, M. L., Eichstaedt, J. C., Kapelner, A., Agrawal, M., Blanco, E., Dziurzynski, L., Park, G., Stillwell, D., Kosinski, M., Seligman, M. E. P., & Ungar, L. H. (2016). Predicting individual well-being through the language of social media. *Biocomputing 2016*, 516–527. https://doi.org/10.1142/9789814749411_0047

Seabrook, E. M., Kern, M. L., Fulcher, B. D., & Rickard, N. S. (2018). Predicting depression from language-based emotion dynamics: Longitudinal analysis of Facebook and Twitter status updates. *Journal of Medical Internet Research, 20*(5), e168. https://doi.org/10.2196/jmir.9267

Stevens, G., O'Donnell, V. L., & Williams, L. (2015). Public domain or private data? Developing an ethical approach to social media research in an interdisciplinary project. *Educational Research and Evaluation, 21*(2), 154–167. https://doi.org/10.1080/13803611.2015.1024010

Stone, L. D., & Pennebaker, J. W. (2002). Trauma in real time: Talking and avoiding online conversations about the death of princess Diana. *Basic and Applied Social Psychology, 24*(3), 173–183. https://doi.org/10.1207/S15324834BASP2403_1

Tackman, A. M., Sbarra, D. A., Carey, A. L., Donnellan, M. B., Horn, A. B., Holtzman, N. S., Edwards, T. S., Pennebaker, J. W., & Mehl, M. R. (2019). Depression, negative emotionality, and self-referential language: A multi-lab, multi-measure, and multi-language-task research synthesis. *Journal of Personality and Social Psychology, 116*(5), 817–834. https://doi.org/10.1037/pspp0000187

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24–54. https://doi.org/10.1177/0261927X09351676

Varghese, C., & Xu, W. (2020). Quantifying what could have been—The impact of the Australian and New Zealand governments' response to COVID-19. *Infection, Disease & Health, 25*(4), 242–244.

Wegwarth, O., Wagner, G. G., Spies, C., & Hertwig, R. (2020). Assessment of german public attitudes toward health communications with varying degrees of scientific uncertainty regarding COVID-19. *JAMA Network Open, 3*(12), e2032335. https://doi.org/10.1001/jamanetworkopen.2020.32335

Supplementary Material

Swiss Federal Council

The Swiss Federal Council is the highest executive power in Switzerland. It is occupied by seven council people (see https://www.admin.ch/gov/en/start.html for more information). To ensure political balance elections follow a rule of thumb (called the 'magic formula' in colloquial language) of how the members must come from each of the biggest parties (social-democratic, Christian, liberal, and populist). All decisions are made jointly and the Federal Council always appears united. For these reasons, we considered the speech of all Federal Council people jointly.

List of Covid-Related Hashtags

General: #China, #2019nCoV, #covid, #COVID19, #COVID-19, #COVID_19, #coronavirus, #corona, #coronav, #coronakrise, #StopCOVID19, #CoronaVirusUpdate,#CoronaVirusUpdates, #SARSCoV2, #CoronaOutbreak, #CoronaVirusOutbreak, #coronavirusupdate, #COVID2019, #Convid19, #WuhanVirus, #CoronavirusPandemic, #Ncov, #N95, #chinesevirus, #fuckingcorona

Specific: #lockdown2020, #Coronapocalypse, #Coronials, #canceleverything, #pneumonia, #neumonia, #wuhan, #pandemic, #stayhome, #InMyQuarantineSurvivalKit, #StayAtHome, #Stayhomestaysafe, #stayhomechallenge, #coronakindness, #SocialDistance, #SocialDistancing, #SocialDistancingNow, #FlattenTheCurve, #flatteningthecurve, #stopthespread, #StayHomeSaveLives, #staythefuckhome, #StayTheFHome, #StopPanicBuying, #PanicShop, #Panicshopping, #panicbuying, #14DayQuarantine, # Duringmy14DayQuarantine, #Quarantine, #Quarantinelife, #lockdown, #shutdownschools, #Healthforall, #KungFlu, #staysafeathome, #staysafe, #shelteringinplace, #covidiot, #epitwitter, #GetMePPE, #wearamask, #DontBeASpreader, #homeoffice, #useamask, #washyourhands, #covidhoax, #covidiots, #hydroxychloroquine, #NoMasks, #scamdemic, #plandemic, #nomaskonme, #wearadamnmask, #nomask, #nomaskmandates, #facemask, #nonewnormal, #newnormal, #masksdontwork, #WuhanPneumonia

German: #BleibtZuhause, #lungenentzündung , #pneumonie , #Quarantäne, #masketragen, #abstandhalten, #Händewashen, #bleibgesund, #maskenpflicht, #andereschützen, #Coronasolidarität, #CoronaSchlager

Country specific: #CoronaInfoCH, #CoronaInfoDe, #covid19de, #CoronaSchweiz, #covid19ch, #coronavirusschweiz, #coronavirusswitzerland, #coronavirusgermany, #coronavirusdeutschland, #coronavirusuk, #coronavirususa, #coronavirusgreatbritain, #CoronaVirusSuisse, #coronavirusswitzerland, #COVID19switzerland, #COVID19UK, #COVID19USA, #COVID19germany, #CoronaGermany, #CoronaDeutschland, #CoronaUS, #CoronaUSA, #CoronaUK, #UKlockdown, #Delockdown,

#CHlockdown, #USlockdown, #USAlockdown, #CDC, #trumppandemic, #ruleofsix, #NHS, #BAG, #ShutDownGermany, #kbf, #keepbritainfree

Table S1. *Overview of adaptations made between the preregistration and the present study*

Planned in preregistration	**Implemented in study**
Research questions: Questions on association between political leader language and collective responses, individual responses, and differences between countries	Research questions: Questions on association between political leader language collective responses. Differences between countries only marginally discussed.
Data: 2 Twitter samples (one with COVID references only one without COVID references), survey data, and public speeches of political leaders	Data: Only one Twitter sample (with tweets referencing COVID only) and public speeches of political leaders
Variables: Political leaders: analytic, positive & negative emotion, immediacy, we-words. Collective: positive emotion, anger, anxiety, sadness, I-talk, we-words, affiliation. Individual responses: positive emotion, negative emotion, anxiety, anger, sadness, I-talk, we-talk, affiliation.	Variables: Political leaders: analytic, positive & negative emotion, immediacy, we-words. Collective: positive emotion, anger, anxiety, sadness, I-talk, we-words.
Cases: cumulative cases of the last 14 days per 100'000	Cases: cumulative cases of the last 14 days per 100'000
Statistical Analysis: Step-wise approach: 1. Plot Twitter language markers over time along with the speeches language markers as well the infection rate/10,000 per country in order to visualize possible effects of the public speeches on the language used on Twitter by the public and the temporal unfolding of this association. 2. Multivariate (discontinuous) Latent Growth Curve. Latent-State-Trait, Latent-Difference, and/or autoregressive models. Cases added as control variable. Cases added as dependent variable in further analysis. Regression model with individual responses as dependent variables. Significance level for all analyses will be set at p < .05, additionally report confidence intervals.	Step-wise approach 1. Correlation analysis between variables 2. Vector autoregressive model. Cases added as control variable. Significance level for all analyses will be set at p < .05, additionally report confidence intervals.
Hypothesis: Hypothesis around specific events. Message adequacy hypothesis Emotional contagion hypothesis Hypothesis around we-words Hypothesis on association between political leader speech and cases Hypothesis around individual responses	Hypothesis: Message adequacy hypothesis Emotional contagion hypothesis Hypothesis around we-words

Figure S1. *Wordclouds of Twitter dataset per country*

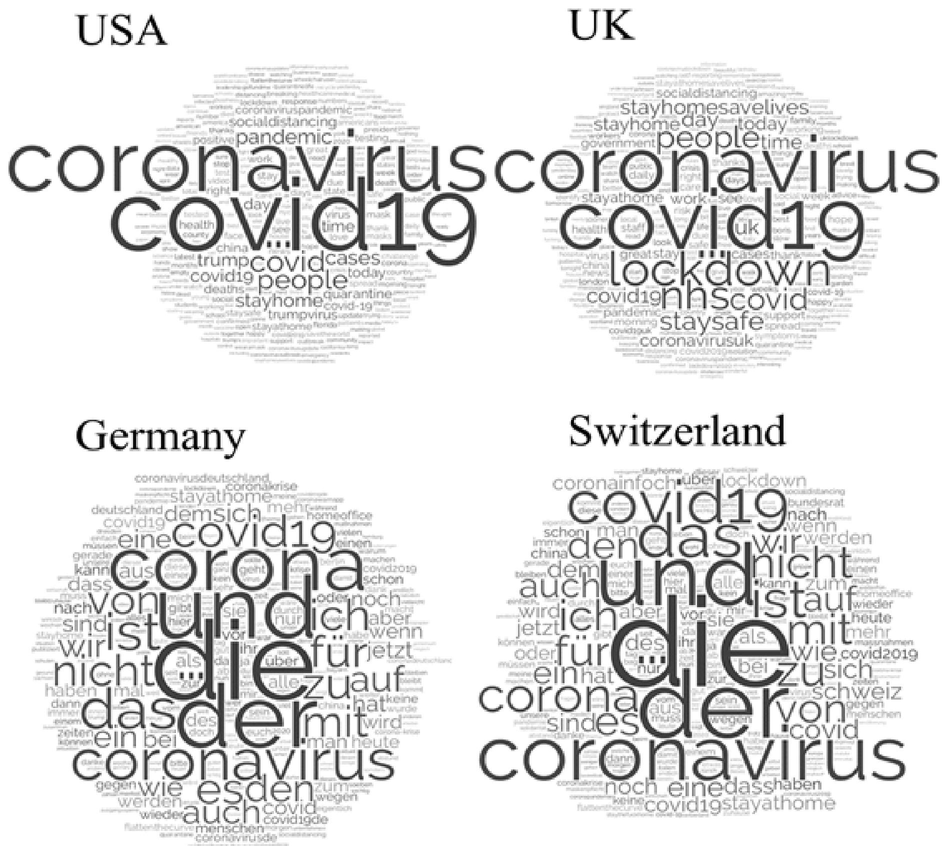

Table S2. *Most frequent words on Twitter per country*

USA		UK		Germany		Switzerland	
Word	Count	Word	Count	Word	Count	Word	Count
covid19	54095	covid19	36953	die	18822	die	1996
coronavirus	44306	coronavirus	34659	der	14415	der	1435
covid	12066	lockdown	18516	und	14213	und	1301
people	10768	nhs	15666	corona	12271	coronavirus	1119
cases	7620	people	10965	coronavirus	8684	das	866
pandemic	7600	covid	10703	das	8528	covid19	853
stayhome	6667	staysafe	8933	ist	7780	ist	708
trump	6384	day	6887	covid19	6500	corona	652
covid-19	6215	uk	6769	zu	6324	nicht	582
time	5500	stayhomesavelives	6683	für	6299	zu	580

Table S3. *VAR(1) coefficients of control variables in overall model (see Table 3 in manuscript)*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Covid-19 infection rates	.13*** [.06;.20]	.14*** [.07;.20]	-.10*** [-.17;-.04]	-.02 [-.10;.06]	.14*** [.06;.23]	.04 [-.04;.10]	.03 [-.01;.07]	.03 [-.01;.06]	-.03 [-.07;.02]	-.02 [-.06;.03]	-.00 [-.05;.05]
Killing G.F. (only US)	-.39*** [-.47;-.29]	-.16*** [-.26;-.06]	-.07 [-.14;.02]	.34*** [.26;.44]	.14*** [.02;.23]	-.10 [-.21;.02]	.02 [-.03;.08]	.00 [-.05;.05]	-.03 [-.10;.04]	-.02 [-.09;.04]	-.01 [-.06;.06]
Johnson infection (only UK)	-.36*** [-.52;-.20]	.28*** [.14;.47]	-.39*** [-.56;-.23]	-.36*** [-.54;-.22]	-.09 [-.24;.08]	-.10 [-.29;.08]	.04 [-.06;.13]	-.00 [-.08;.08]	.00 [-.10;.11]	.06 [-.03;.16]	.02 [-.07;.11]
UK	.06 [-.10;.27]	-.35*** [-.60;-.15]	.33*** [.12;.49]	.56*** [.40;.74]	.17 [-.01;.32]	.02 [-.14;.19]	-.03 [-.14;.10]	.02 [-.07;.10]	-.01 [-.14;.11]	-.06 [-.17;.05]	-.02 [-.11;.09]
DE	-.27*** [-.39;-.13]	-.11 [-.23;.03]	-.05 [-.13;.05]	.24*** [.15;.32]	.09 [-.01;.21]	-.07 [-.17;.05]	.01 [-.05;.08]	.01 [-.06;.08]	-.01 [-.09;.04]	.00 [-.06;.06]	-.01 [-.07;.04]
CH	-.25*** [-.36;-.17]	-.10 [-.21;.01]	-.04 [-.15;.04]	.24*** [.15;.36]	.10 [-.01;.21]	-.07 [-.19;.03]	.02 [-.03;.09]	.01 [-.05;.07]	-.01 [-.07;.06]	.01 [-.06;.07]	.01 [-.07;.05]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. p values are computed by averaging distribution of p values (Gelman, 2005). 95% CIs in square brackets.

Table S4. *VAR(1) Model: USA*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk t-1	.31*** [.19;.41]										.08 [-.02;.18]
Twitter positive emotion t-1		.30*** [.17;.43]					-.01 [-.14;.08]		.09 [-.07;.24]	.05 [-.05;.11]	
Twitter anxiety t-1			.45*** [.32;.57]				.01 [-.13;.13]	-.02 [-.15;.08]	.02 [-.17;.18]	-.07 [-.18;.05]	.11 [-.06;.20]
Twitter anger t-1				.11 [-.04;.25]					-.06 [-.15;.10]	-.02 [-.09;.08]	
Twitter sadness t-1					.11 [-.02;.24]		.07 [-.05;.18]	-.11** [-.21;-.02]	-.01 [-.12;.14]	-.04 [-.14;.05]	
Twitter we t-1						.13*** [.01;.25]		.04 [-.05;.12]		.05 [-.02;.11]	
Leader positive emotion t-1		-.11 [-.32;.07]	.09 [-.14;.30]		-.10 [-.32;.14]		.66*** [.53;.74]				
Leader negative emotion t-1			.17 [-.11;.31]		-.20 [-.37;.04]	.02 [-.17;.18]		.69*** [.58;.75]			
Leader we t-1		.10 [-.06;.27]	-.00 [-.16;.16]	-.05 [-.17;.09]	-.14 [-.31;.02]				.49*** [.36;.59]		
Leader analytic t-1		-.03 [-.20;.19]	-.01 [-.25;.21]	.18 [-.01;.35]	-.06 [-.27;.08]	.12 [-.06;.30]				.65*** [.59;.72]	
Leader immediacy t-1	-.00 [-.12;.15]		-.06 [-.24;.12]								.58*** [.50;.65]
Covid-19 infection rates	-.09 [-.21;.07]	.15 [-.06;.31]	-.27*** [-.40;-.09]	-.06 [-.24;.09]	.32*** [.14;.48]	-.21 [-.38;.02]	.05 [-.14;.23]	.08 [-.26;.05]	.00 [-.22;.21]	-.04 [-.21;.09]	-.06 [-.20;.13]
Killing G.F. (only US)	-.37*** [-.49;-.22]	-.21*** [-.36;-.03]	.06 [-.11;.20]	.54*** [.37;.71]	.06 [-.13;.23]	.01 [-.15;.21]	.01 [-.14;.17]	.13 [-.03;.26]	-.12 [-.29;.06]	-.03 [-.17;.13]	.07 [-.13;.20]
R^2	.46*** [.35;.57]	.22*** [.14;.34]	.39*** [.26;.48]	.30*** [.22;.39]	.32*** [.21;.42]	.12*** [.04;.23]	.50*** [.36;.60]	.56*** [.47;.66]	.38*** [.28;.46]	.55*** [.48;.61]	.39*** [.30;.46]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. p values are computed by averaging distribution of p values (Gelman, 2005). 95% CI in square brackets. .Posterior-predictive-p value of entire model = .000, 95% CI for difference between observed and replicated X^2 = [156.39; 257.69]

Table S4. *VAR(1) Model: UK*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk t-1	.26*** [.15;.37]										-.01 [-.06;.04]
Twitter positive emotion t-1		.31*** [.15;.45]					.09*** [.04;.15]		.08** [.01;.15]	.03 [-.02;.09]	
Twitter anxiety t-1			.27*** [.15;.38]				.10** [.05;.18]	.12** [.03;.20]	.13** [.04;.22]	.15** [.04;.22]	-.06 [-.14;.02]
Twitter anger t-1				.01 [-.11;.17]					-.01 [-.05;.04]	-.01 [-.05;.04]	
Twitter sadness t-1					.03 [-.11;.17]		.02 [-.05;.07]	-.01 [-.08;-.03]	.01 [-.05;.06]	-.00 [-.05;.05]	
Twitter we t-1						.20*** [.07;.33]		.03 [-.04;.07]		.00 [-.05;.05]	
Leader positive emotion t-1		-.16 [-.06;.32]	-.06 [-.25;.12]		.10 [-.24;.38]		.94*** [.88;.99]				
Leader negative emotion t-1			.03 [-.13;.13]		-.06 [-.23;.19]	.05 [-.10;.19]		.91*** [.88;.94]			
Leader we t-1		.04 [-.06;.18]	-.15* [-.29;-.02]	-.06 [-.17;.08]	.05 [-.14;.21]				.92*** [.88;.95]		
Leader analytic t-1		.16 [-.04;.35]	-.31*** [-.46;-.10]	-.08 [-.27;.12]	.13 [-.20;.36]	.36*** [.18;.55]				.96*** [.90;1.02]	
Leader immediacy t-1	-.01 [-.16;.14]		.04 [-.09;.14]								.94*** [.90;.97]
Covid-19 infection rates	.40*** [.28;.54]	.14 [-.03;.29]	-.06 [-.19;.09]	-.06 [-.23;.05]	.23 [-.02;.43]	.15* [.00;.02]	-.01 [-.07;.09]	.04 [-.05;.09]	-.01 [-.07;.06]	.00 [-.05;.06]	-.01 [-.07;.07]
Johnson infection	-.41*** [-.52;-.29]	.07 [-.10;.21]	-.18*** [-.32;-.05]	-.20*** [-.39;-.04]	-.28*** [-.49;-.06]	.35*** [-.50;-.19]	.02 [-.07;.09]	.06 [-.03;.14]	.05 [-.02;.14]	.07 [-.02;.15]	-.04 [-.14;.02]
R^2	.40*** [.30;.48]	.38*** [.37;.55]	.65*** [.57;.72]	.14*** [.06;.22]	.14*** [.07;.22]	.20*** [.10;.29]	.88*** [.85;.91]	.82*** [.78;.86]	.83*** [.80;.86]	.87*** [.85;.90]	.88*** [.86;.90]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. p values are computed by averaging distribution of p values (Gelman, 2005). 95% CI in square brackets. .Posterior-predictive-p value of entire model = .000, 95% CI for difference between observed and replicated X^2 = [-.19.37; 120.83].

Table S4. *VAR(1) Model: DE*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk t-1	.15*** [.00;.25]										-.02 [-.05;.01]
Twitter positive emotion t-1		.03 [-.05;.19]					-.02 [-.09;.05]		.02 [-.02;.07]	.01 [-.03;.05]	
Twitter anxiety t-1			.19*** [.06;.30]				.05 [-.02;.11]	-.08** [-.14;-.02]	-.07** [-.13;-.01]	.01 [-.06;.08]	-.01 [-.07;.06]
Twitter anger t-1				.01 [-.11;.15]					-.02 [-.06;.03]	.02 [-.02;.06]	
Twitter sadness t-1					.11 [-.05;.22]		-.06** [-.11;-.01]	.08** [.02;.13]	.03 [-.02;.09]	-.00 [-.04;.03]	
Twitter we t-1						.09 [-.04;.22]		-.01 [-.05;.05]		.01 [-.02;.05]	
Leader positive emotion t-1		.10 [-.17;.20]	-.29*** [-.49;-.08]		.11 [-.29;.11]		.92*** [.89;.95]				
Leader negative emotion t-1			-.15 [-.29;.03]		-.08 [-.22;.17]	.03 [-.14;.18]		.86*** [.82;.89]			
Leader we t-1		.20 [-.06;.40]	-.07 [-.35;.13]	-.09 [-.27;.14]	-.04 [-.29;.21]				.86*** [.82;.89]		
Leader analytic t-1		-.00 [-.17;.16]	.20 [-.09;.43]	.05 [-.19;.23]	.12 [-.08;.30]	.05 [-.10;.20]				.91*** [.88;.94]	
Leader immediacy t-1	.01 [-.12;.14]		.26 [-.00;.49]								.90*** [.86;.92]
Covid-19 infection rates	.11 [.04;.24]	.13 [-.01;.27]	.01 [-.17;.15]	.01 [-.13;.19]	-.00 [-.16;.16]	.13* [.01;.28]	.00 [-.05;.07]	.04 [-.04;.09]	-.02 [-.04;.07]	.03 [-.09;.03]	-.01 [-.08;.06]
R^2	.05*** [.01;.12]	.10*** [.04;.20]	.24*** [.15;.32]	.03*** [.00;.06]	.07** [.02;.14]	.05*** [.02;.14]	.84*** [.80;.87]	.81*** [.77;.84]	.82*** [.78;.85]	.83*** [.79;.86]	.81*** [.76;.83]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. p values are computed by averaging distribution of p values (Gelman, 2005). 95% CI in square brackets. .Posterior-predictive-p value of entire model = .000, 95% CI for difference between observed and replicated X^2 = [-.19.37; 120.83].

Table S4. *VAR(1) Model: CH*

	Twitter I-talk	Twitter positive emotion	Twitter anxiety	Twitter anger	Twitter sadness	Twitter we	Leader positive emotion	Leader negative emotion	Leader we	Leader analytic	Leader immediacy
Twitter I-talk t-1	.02 [-.13;.18]										.04 [-.01;.08]
Twitter positive emotion t-1		-.03 [-.19;.10]					.01 [-.10;.11]		.01 [-.05;.07]	.05 [-.03;.11]	
Twitter anxiety t-1			-.04 [-.17;.08]				.02 [-.10;.11]	.02 [-.07;.11]	-.05 [-.14;.02]	.02 [-.08;.11]	.00 [-.08;.09]
Twitter anger t-1				-.09 [-.23;.04]					-.04 [-.12;.06]	.01 [-.08;.08]	
Twitter sadness t-1					-.00 [-.19;.14]		-.00 [-.11;.10]	.00 [-.06;.05]	-.00 [-.07;.07]	-.04 [-.11;.05]	
Twitter we t-1						.02 [-.12;.22]		.02 [-.03;.07]		-.06 [-.13;.02]	
Leader positive emotion t-1		.07 [-.09;.23]	.07 [-.10;.24]		-.04 [-.20;.16]		.74*** [.68;.78]				
Leader negative emotion t-1			.12 [-.08;.37]		-.05 [-.26;.12]	.18*** [.05;.29]		.85*** [.81;.87]			
Leader we t-1		-.04 [-.18;.13]	.08 [-.10;.25]	-.07 [-.23;.11]	-.22** [-.42;-.03]				.84*** [.80;.87]		
Leader analytic t-1		-.05 [-.22;.12]	-.00 [-.22;.20]	-.00 [-.17;.17]	-.13 [-.29;.01]	-.11 [-.28;.07]				.75*** [.70;.79]	
Leader immediacy t-1	.03 [-.14;.16]		.10 [-.08;.33]								.84*** [.80;.87]
Covid-19 infection rates	.16 [-.03;.29]	.06 [-.11;.21]	.09 [-.08;.22]	.20** [.03;.34]	-.09 [-.23;.04]	-.04 [-.15;.14]	.04 [-.06;.14]	-.02 [-.08;.05]	.01 [-.08;.07]	-.00 [-.09;.08]	.02 [-.07;.10]
R^2	.03*** [.01;.12]	.03*** [.00;.09]	.06*** [.02;.13]	.06*** [.02;.12]	.08*** [.02;.15]	.05*** [.02;.11]	.56*** [.49;.63]	.72*** [.67;.76]	.72*** [.67;.78]	.59*** [.52;.64]	.73*** [.68;.77]

Note. *** $p < .001$; ** $p < .01$; * $p < .05$ and 95% CI which do not contain 0. p values are computed by averaging distribution of p values (Gelman, 2005). 95% CI in square brackets. .Posterior-predictive-p value of entire model = .000, 95% CI for difference between observed and replicated X^2 = [31.91; 142.00].