When danger strikes: A linguistic tool for tracking America’s collective response to threats

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In today’s vast digital landscape, people are constantly exposed to threatening language, which attracts attention and activates the human brain’s fear circuitry. However, to date, we have lacked the tools needed to identify threatening language and track its impact on human groups. To fill this gap, we developed a threat dictionary, a computationally derived linguistic tool that indexes threat levels from mass communication channels. We demonstrate this measure’s convergent validity with objective threats in American history, including violent conflicts, natural disasters, and pathogen outbreaks such as the COVID-19 pandemic. Moreover, the dictionary offers predictive insights on US society’s shifting cultural norms, political attitudes, and macroeconomic activities. Using data from newspapers that span over 100 years, we found change in threats to be associated with tighter social norms and collectivistic values, stronger approval of sitting US presidents, greater ethnocentrism and conservatism, lower stock prices, and less innovation. The data also showed that threatening language is contagious. In all, the language of threats is a powerful tool that can inform researchers and policy makers on the public’s daily exposure to threatening language and make visible interesting societal patterns across American history.

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Significance

People are constantly exposed to threatening language in mass communication channels, yet we lack tools to identify language about threats and track its impact on human groups. We developed a threat dictionary, a computationally derived linguistic tool that indexes threat levels from texts with high temporal resolution, across media platforms, and for different levels of analysis. The dictionary shows convergent validity with objective threats in American history, including violent conflicts, natural disasters, and pathogen outbreaks. Moreover, fluctuations in threat levels from the past 100 years coincide with America’s shifting cultural norms, political attitudes, and macroeconomic activity, demonstrating how this linguistic tool can be applied to understand the collective shifts associated with mass communicated threats.

Author contributions: V.K.C. and M.J.G. designed research; V.K.C., S.S., X.P., and M.J.G. performed research; V.K.C. and X.P. analyzed data; and V.K.C., M.J.G., and X.P. wrote the paper.

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official write-ups (15, 16). Consequently, only relying on a single WEM would limit our sampling of words. To ensure we identified threat words expressed in multiple communication settings, we used an ensemble of WEMs, each separately pretrained on a unique corpus: 1) Wikipedia articles, 2) Twitter posts, and 3) Common Crawl’s randomized sample of web pages (GloVe) (14). Wikipedia provides encyclopedic content, whereas Twitter posts are real-time interactions on social media. The third model trained on Common Crawl’s metadata of eclectic web pages represents language applied in a broad spectrum of contexts. Drawing from all three WEMs, we extended our lexical sampling and capacity to glean threat terms common across a variety of communication channels.

SI Appendix, Table S1 provides the pseudocode (algorithmic flow) of our dictionary development’s 10-step process. First, after loading all three of the pretrained WEMs, we identified words proximal to “threat” as well as its synonyms within each model. From this word generation, we filtered out common words, such as “the,” “of,” and “all.” This produced the first list of words \( x_1, \ldots, x_n \) semantically associated with threat. Before vetting this list, we applied spectral clustering from each word’s vector coordinates to evaluate how they were interrelated (17, 18). The spectral clustering process involved computing a matrix based on closeness as a measure of similarity \( S_{ij} \geq 0 \) between all possible word pairings \( x_i \) and \( x_j \) from the list. An optimal number of segmentation points was determined from this spatial distance information to cluster together similar words and divide up dissimilar words. The resulting clusters brought disambiguation and clarity to the extracted words, thereby providing more contextual information.

Following these steps, based on a predefined exclusion criterion, inapposite clusters of words were removed if full interrater agreement was achieved between the study’s authors. For example, we excluded clusters predominately made up of foreign words, numbers, or named entities (Europe, Gaza, Balkan). We repeated these steps with the two other WEMs. The final threat dictionary was composed of terms \( n = 240 \) that converged across all three model outputs. A sample of these final threat terms includes “attack,” “crisis,” “destroy,” “disaster,” “dead,” “violent,” “injuries,” “lethal,” “looming,” “meltdown,” “outbreak,” “suffer,” “tension,” “toxic,” “unrest,” “unstable,” and “violent.” SI Appendix, Table S2 provides the full dictionary.

Analysis of textual documents using the threat dictionary can be performed here: https://bit.ly/3zp2cYi. We next set out to examine the convergent validity of the threat dictionary by showing how patterns of change in the use of threat words over time correspond to real moments in US history when Americans faced grave threats. We applied our threat dictionary to time-stamped news articles from 1900 to 2020 via https://www.Newspapers.com (19). As the largest online repository of historical and contemporary newspapers, this publicly available data source contains over 600 million pages of digitized news content. We tallied the occurrence rates of threat dictionary terms in news articles at monthly and annual intervals at both the state and national levels. Since these estimates can be influenced by the number of newspapers published within a given time, we adjusted these total counts by the coinciding approximate number of article pages published. This produced our primary time series dataset, which we used to track variance in threat levels over the past century of US history.

We first examined longitudinal descriptive trends in threat levels over the last 100 years of US history based on our threat index computed from https://www.Newspapers.com. Extant theories and data-driven works by numerous scholars (20–23) have argued that threat levels are in historical decline. Here, we examined whether threat levels do appear to be decreasing across US newspapers over time by modeling the monthly increases with time as a predictor. As portrayed in Fig. 1, discussion of threats in American newspapers has been in steady decline \( B = -0.02, 95\% \ CI \ [ -0.024, -0.022], P < 0.001 \), with this linear temporal trend accounting for 65% of the variance in the series. Since an ordinary least squares estimation with time series data is prone to self-correlating residuals, we fitted a model with optimal autoregressive integrated moving average (ARIMA) errors (24–26). The gradual decrease in US threat levels from 1900 to 2020 remained significant \( B = -0.002, 95\% \ CI \ [ -0.003, -0.001], P < 0.001 \), accounting for 98% of the ARIMA-adjusted series variance. ARIMA models are also beneficial for making forecasts since they capture both the autocorrelation and nonlinear trends in the series (27). Applying the same ARIMA parameters determined earlier, we forecasted the threat series two decades into the future (2020 to 2040). Unlike a linear approximation of predicted values, the mean predictions from the ARIMA-based forecasts indicate threat levels may rise in the coming decades, reflecting the positive trend in threat levels from the past eight years (Fig. 1). However, the wide prediction bounds indicate that this trend is uncertain and should be interpreted with caution, especially because irregular and unpredictable future events can affect such forecasts.

We also sought to validate the threat dictionary by demonstrating its convergence with actual life-threatening events. We focused on three domains of socioecological threats that have indiscriminately endangered human life throughout history: violent conflicts, natural disasters, and pathogen outbreaks. When these collective dangers increase at a certain time or region in US history, more words related to threats are expected to increase in mass communication channels as well. The data taken as our ground truth were times the United States became involved in militaristic conflicts since 1900. Federal Emergency Management Agency (FEMA) reports on severe natural disaster cases from 1953 to 2020, and data on regional mortality rates due to major infectious diseases from the Institute for Health Metrics and Evaluation (IHME) from 1980 to 2014. Additionally, in the early months of 2020 as the
severity of the COVID-19 pandemic escalated, we analyzed 0.24 million Twitter posts sampled from each US state daily for 56 days. This dataset enabled us to examine the real-time threat dynamics relevant to the unfolding COVID-19 pandemic. Testing a variety of convergent indicators was critical to assessing the measure’s sensitivity to multiple types of major collective threats and its application across different platforms.

Lastly, our 100-year plus threat data indexed from US newspapers enabled our historical analysis of national correlates with threats. In times of great danger, both preindustrial and contemporary societies have galvanized their populations with more structure and cooperation to better withstand collective threats (28–30). Thus, heightened periods of threat in US history are expected to coincide with shifts in America’s increased preference for order—stronger norms, group orientation, and conservatism—yet lower levels of openness and innovation. Specifically, we examine how changes in threat levels correspond to an array of changes in cultural norms (cultural tightness and collectivism), political shifts (approval of sitting US presidents, Republican identification, and anti-immigrant attitudes), and macroeconomic activities (changes in the US stock market and innovation rates).

**Results**

**War and Conflicts.** Although US news coverage of threats is in gradual decline, we expected to find momentary increases in threat words during times of foreign conflict, such as major wars and attacks on US soil. We considered numerous wars from the past century that jointly provided sufficient coverage of America’s major militaristic embroilments, including US involvement in World War I (WWI), World War II (WWII), the attack on Pearl Harbor, the Korean War, the Vietnam War, the Gulf War, the September 11th terrorist attacks, and the Iraq War. Discontinuous growth models (DGMs) (31) enabled the estimation of these upticks in threat levels when major conflicts occurred. DGMs test the change in trajectory of a given variable measured over time and its interrupted response pattern due to a specified shock, relative to the times directly preceding the shock. We conducted a DGM analysis per event, with each base model including three time-related covariates that reflect threat frequencies 5 mo before (prethreat), during (onset), and 5 mo after (postthreat) the advent of a conflict. SI Appendix, Table S4 illustrates an example of how these time predictors are coded. In our DGMs, the onset points were designated based on the official dates of these ordeals (SI Appendix, section C has details). This onset vector, also referred to as the transition or time change variable, tests how the intercept has changed right after an expected event. For our research purposes, we anticipated that this onset time estimate for threat levels would reflect a significant discontinuity (i.e., an increase) after each foreign conflict, relative to the expected change pattern prethreat.

Our results, summarized in SI Appendix, Table S6, indicated that the intercepts for locally reported threat words in newspapers significantly increased as compared with their expected projections following news of WWI (P < 0.001), WWII (P < 0.001), the attack on Pearl Harbor (P < 0.001), the Korean War (P < 0.001), the Vietnam War (P < 0.001), the Gulf War (P < 0.001), the “war on terror” instigated by the September 11th terrorist attacks (P < 0.001), and the Iraq War (P < 0.001). For all conflicts, we found that the intercepts of threat levels among statewide newspapers significantly increased in threat words at the onset of the conflict relative to its prior trajectory (Fig. 2). To put the results in context, threat language in newspapers during the onset of WWII increased by 0.43 points from its expected levels prior to the start of WWII. At the transition time of WWII’s start, threat increased by 0.15 points. The Pearl Harbor attack led to a 0.16-point increase in threat. At the start of the Korean War, threat values jumped to 0.30 points. Threat rose by 0.18 points when Congress passed a resolution to increase
military presence in Vietnam and by 0.36 points when the Gulf War started. The September 11th terrorist attacks escalated threat levels by 0.16 points. At the onset of the Iraq War, threat levels increased by 0.21 points.

**Natural Disasters.** Next, we examined whether the threat dictionary is sensitive to the occurrence of objective natural disasters. The counts of major disaster declarations (MDDs) from FEMA reflect emergency response efforts instituted to help local governments combat severe natural events, such as tsunamis, earthquakes, tornadoes, hurricanes, flash floods, snowstorms, droughts, fires, and volcanic eruptions. We compiled FEMA’s available monthly data on the number of MDDs enacted for each US state across the last 60 years and conducted a multilevel regression with data nested by states. This analysis was conducted at the state level, with MDDs likely varying based on each state’s distinct ecological vulnerabilities. We found that greater instances of MDDs within each state were predictive of more threat words found in local statewide newspapers ($B = 0.003$, $P < 0.001$, 95% CI [0.002, 0.004], $R^2 = 0.24$).

**Pathogens.** Finally, we examined whether threat language in newspapers can be related to greater rates of pathogen-related deaths. Estimates of death rates from contagious diseases are documented in HMHE’s available state-level data spanning 35 years (1980 to 2014). Annual average death rates were computed per state by collapsing together mortality rates from all categories of major infectious diseases (hepatitis, HIV/AIDS, diarrheal diseases, lower respiratory infections, meningitis, and tuberculosis). The results showed a positive association with threat words and increases in mortality rates from infectious diseases ($B = 0.10$, $P < 0.001$, 95% CI [0.07, 0.12], $R^2 = 0.37$). SI Appendix, Table S7 presents the results of the multilevel analysis for both infectious disease deaths and MDDs.

We also examined whether the threat dictionary can capture the growing severity of the COVID-19 pandemic. As more people in the United States were affected by COVID-19 in 2020, we tested how this growing public health crisis, measured by the number of cases and deaths, coincides with more threat words found in people’s real-time tweets. We matched the time-stamped and geolocated tweets in our sample to its corresponding state’s available pandemic statistics. Following the data processing detailed in SI Appendix, section B2, we matched the remaining 105,209 tweets to the corresponding daily statewide number of COVID-19 cases and deaths from March to May 2020. Since both cases and deaths were highly positively skewed, they were log transformed. We used negative binomial regression to account for the overdispersed distribution of threat words ($M = 0.39$, $SD = 0.68$) (32). The results of our analysis revealed how threat words found in tweets increased as both COVID-19 cases (incident rate ratio [IRR] = 1.02, 95% CI [1.01, 1.02], $P < 0.001$) and deaths (IRR = 1.02, 95% CI [1.02, 1.03], $P < 0.001$) grew in number. On average, 4% more threat words appeared per tweet with every 10-factor increase in positive cases, and 5% more threat words appeared with every 10-factor increase in deaths.

For emergent validity, we performed a supervised machine learning classification test, wherein a random forest model was trained to identify tweets on the topic of COVID-19 ($n = 105,348$) against tweets unrelated to COVID-19 ($n = 133,313$). The model made these classifications based on how often words from different dictionaries were found in a particular tweet. This included the threat dictionary and other dictionaries with nomological overlap to threats, such as dictionaries on death, risk, negative emotion (12), and moral foundations (33). More detail on this analysis is described in SI Appendix. SI Appendix, Fig. S1 shows how, as compared with other dictionaries, the threat dictionary exhibited the highest feature importance for classification purposes, supporting its capacity to accurately distinguish threats in real-time broadcasted content.

We also examined whether threatening language is contagious. On Twitter, retweets involve people sharing a tweet to their own extended network (34). Based on previous research, we ran a negative binomial regression and tested whether the number of threat terms in a tweet is predictive of its retweet rate, while holding constant a number of twitter covariates as in ref. 32, including a user’s number of followers, URLs found in the tweet, and the verified status of the user. We found that tweets on COVID-19 that expressed more threat terms accrued more retweets (IRR = 1.18, 95% CI [1.15, 1.21], $P < 0.001$). On average, adding a single threat word to a tweet increased its expected retweet rate by 18%, indicative of the contagious properties of threat words on social media. Given that previous research (32) found that tweets high in moral-emotional words were more likely to be retweeted, we also tested whether our threat measure predicted retweets above and beyond the moral–emotional measure. We replicated the same analytical procedure with the same covariates found in previous research (32) and used measures of both threat and moral–emotional words as predictors in our model. After controlling for the effects of moral–emotional words, adding a single threat word to a tweet increased its expected retweet rate by 15% (IRR = 1.15, 95% CI [1.12, 1.19], $P < 0.001$). These results, further described with additional robustness tests in SI Appendix, suggest that linguistic cues that elicit a potential threat possess the rhetorical advantage of garnering people’s attentional interest and can spread to more people. Particularly in times of public crises, the contagious nature of threat-laden online messages has important bearing on urgent issues regarding social media’s role in amplifying misinformation campaigns and mass panic, a point we return to in Discussion.

Having demonstrated how our threat measure coincides with actual threats in US history, we next examined its predictive power. Specifically, we applied our long-run data tracking national fluctuations in threat levels from newspapers to assess corresponding shifts in America’s cultural, political, and economic standing over time.

For this analysis, we addressed common problematic features of time series data structures, including serial dependence, and lagged forecast errors that can result in spurious findings. To do this, we fitted ARIMA models to test the linear approximation of these relationships, with adjustments made to the error terms that address these temporal dependencies (26). Three main parameters ($p, d, q$) are specified for the ARIMA errors. The $p$ component denotes the number of lags that account for the autoregressive structure of the model, the $d$ parameter refers to the order of differencing needed to stabilize the variance in the time series, and the $q$ term represents the moving average value that explains the model’s lagged random errors. For our data collected at monthly intervals, the same three parameters were extended to capture any seasonal influences, noted in capitalized form ($P, D, Q$). Identification of parameters for our ARIMA models was obtained using an algorithm (24) that systematically searches for the optimal combination of parameters with the least fitting error based on the Akaike information criterion (AIC). The ARIMA model classification and results are presented in Table 1.

**Cultural Shifts.** Research on the evolution of human culture demonstrates how groups adjust and adapt their attitudes and norms in accordance with changing environmental demands (35). Past studies have shown how cultures with a history of ecological and human-made threats (invasions, natural disasters, and pathogens) are higher ontightness (i.e., have strictly enforced social norms and low tolerance for deviant members)
Table 1. Results of regression with ARIMA errors

| Indicator | (p, d, q) (P, D, Q)* | B (SE) | t    | p    | (p, d, q) (P, D, Q)* | B (SE) | t    | p    |
|-----------|-----------------------|--------|------|------|-----------------------|--------|------|------|
| Tightness | (1, 1, 1) (2, 0, 0)   | 0.08 (0.02) | 5.28 | <0.001 | (1, 1, 1) (2, 0, 0)   | 0.09 (0.02) | 5.46 | <0.001 |
| Collectivism | (2, 1, 2) (0, 0, 2) | 0.35 (0.05) | 9.97 | <0.001 | (0, 1, 2) (0, 0, 2)   | 0.56 (0.06) | 10.14 | <0.001 |
| Anti-immigration | (0, 1, 0) | 0.03 (0.12) | 3.02 | <0.01 | (1, 0, 0) | 0.34 (0.12) | 2.90 | <0.01 |
| Presidential approval | (2, 1, 2) (0, 0, 2) | 0.06 (0.02) | 3.19 | <0.01 | (1, 0, 2) (0, 0, 2) | 0.06 (0.02) | 3.14 | <0.01 |
| Republican partisanship | (0, 1, 0) | 0.24 (0.12) | 2.05 | 0.04 | (1, 0, 1) | 0.20 (0.11) | 1.70 | 0.09 |
| S&P 500 | (3, 2, 1) | -0.01 (0.003) | -4.07 | <0.001 | (0, 2, 4) | -0.01 (0.003) | -4.00 | <0.001 |
| DJIA | (3, 1, 0) (2, 1, 0) | -0.03 (0.01) | -4.85 | <0.001 | (0, 2, 1) | -0.02 (0.004) | -4.07 | <0.001 |
| NASDAQ | (5, 2, 4) (0, 0, 2) | -0.01 (0.004) | -2.24 | 0.03 | (2, 2, 3) (0, 0, 2) | -0.01 (0.004) | -2.38 | 0.02 |
| Patents | (2, 2, 2) | -0.10 (0.03) | -3.51 | <0.001 | (1, 1, 1) | -0.12 (0.03) | -3.96 | <0.001 |

The set of results on the left features the parameters and coefficients from ARIMA models with only threat as a predictor. Estimates presented on the right side of the table belong to models with threat as a predictor, in addition to controlling for real GDP per capita.

*The ARIMA model parameters are specified by its nonseasonal components (p, d, q) and seasonal components (P, D, Q). For example, we fit a regression with ARIMA (2, 2, 2) errors for the model regressing patent numbers on threat levels over time.

(36, 37). Likewise, ecological disasters have been correlated with cultural collectivism or greater group orientation that supersedes individualistic priorities (38, 39). We tested these relationships with a more expansive conceptualization of threats as they have taken place over time. We expected variance in threat levels in the United States to be associated with shifts in America’s tight and collectivistic leanings. To quantify the set of results on the left features the parameters and coefficients from ARIMA models with only threat as a predictor. Estimates presented on the right side of the table belong to models with threat as a predictor, in addition to controlling for real GDP per capita.

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prices of the three major market indices listed on the US stock exchange: the Standard and Poor (S&P) 500, the Dow Jones Industrial Average (DJIA), and the National Association of Securities Dealers Automated Quotations (NASDAQ) Composite. Daily price returns were averaged at monthly intervals from the start of each stock’s established indices up to December 2020. For example, data on the S&P 500 were collected from 1957 when the index first became a 500-stock composite to the end of 2020 (66). DJIA performance was measured from 1928 to 2020, and we collected the closing prices of the NASDAQ from 1971 to 2020. Lastly, we indexed the number of utility patent applications from 1900 to 2019. This annual count is provided by the US Patent and Trademark Office (USTO) for utility patents, which include new inventions and improvements to existing products from 1900 to 2019. Patent counts have been commonly used in past studies as a national measure of inventive activities and potential for creativity (40, 67). We found that greater threat levels in newspapers were significantly negatively associated with stock market returns for the S&P 500 ($B = -0.01, 95\% \text{ CI } [-0.24, -0.04], P < 0.001$), DJIA ($B = -0.03, 95\% \text{ CI } [-0.04, -0.02], P < 0.001$), and NASDAQ ($B = -0.01, 95\% \text{ CI } [-0.02, -0.001], P < 0.05$). Increases in threat were also negatively related to the number of USTO-reported patent applications ($B = -0.10, 95\% \text{ CI } [-0.15, -0.04], P < 0.001$).

Table 1 summarizes the results of these ARIMA models and shows how the relationship between threat and these indicators remained significant even after controlling for real gross domestic product (GDP) per capita, except for Republican Party partisanship. We also provide correlational results in SI Appendix, Table S8 to demonstrate alternative methods for examining these joint processes.

To understand the directionality of these cross-temporal relationships, Granger tests of predictive causality were next conducted to study whether threat levels precede these cultural, political, and economic changes. Given two time series, Granger causality models test whether past values of a predictor variable can explain the changing outcome of another variable over and beyond the ability of this outcome variable’s prior observations predicting its own future values (68). Across two sets of Granger analyses, two potential directional possibilities were tested with 1) threat modeled as a predictor and 2) threat modeled as an outcome. In the first model, if threat significantly predicts a societal outcome, while the reverse direction is not significant in the second model, these two sets of results provide strong evidence of a specific temporal ordering wherein changes in a societal outcome likely follow threats. If the second model is significant, but the first model is not, this would indicate that changes in threat levels likely follow a societal trend. When both models are significant, this can indicate bidirectionality or possible influence of an exogenous variable causing changes to both series.

To conduct Granger tests, we removed the time dependencies from each individual series using the previously described ARIMA procedure and then, extracted the residuals from each series. Table 2 summarizes the findings of our Granger tests at a select lag of up to 5 years, as with the lag specifications of previous research (see refs. 38 and 40). Following a model comparison of all lags possible for up to a period of 5 years, the reported models correspond to the lag lengths representing the best model fit according to AIC estimates.

The results indicated that, under the optimal lag of our threat measure, threat levels significantly predicted cultural tightness, collectivism, the S&P 500, and the DJIA—over and beyond lagged values of the criterion predicting its own current values. The reverse directionality was also found to be significant for these indicators. For example, just as stock market performance suffers from news of threats, stock market downturns themselves would also instate a national financial threat. Meanwhile, lags of threat significantly predicted NASDAQ outcomes, whereas the reverse direction was not significant. While significantly correlative, our Granger models showed no significant lagged causal links, modeled in both directions, between threat and the remaining indicators. This could suggest a periodicity issue wherein directionality is sensitive to high-frequency monthly data. For example, data on changes in the percentage of Republican Party affiliates, anti-immigration views, and patents numbers were assessed at annual levels based on available data. It is possible that these societal indicators are fast changing or quick to normalize, thereby explaining why directionality would not be captured by low-frequency yearly lags.

Discussion

A primary goal of the present study was to show how language can be harnessed to estimate when diverse threats occur throughout history and their effects on societal culture, politics, and macroeconomic activity. Our dictionary development process introduced the application of multimodel computational techniques to identify threat-relevant words and clustering methods to inform the final threat dictionary. We also validated our threat dictionary based on its convergence with documented threats that occurred in real life, demonstrating the measure’s sensitivity to major categories of threats, including wars, pathogen stress, and natural disasters. The convergence between these resulting threat indices and actual high-threat events over time supports the stability and generalizability of our threat measure.

Our linguistic tool offers predictive insights into societal responses to mass communicated threats. Using several time series analytical methods, we demonstrated how historical patterns in threat levels coincided with stock market trends, conservative political attitudes, presidential approval numbers, and changing cultural norms. This is an attempt to empirically examine different cultural, political, and economic cross-temporal effects at once using one comprehensive measure of threat over many time points. While the current study’s scope is limited to the English language, especially as it relates to dynamics found in the United States, this work’s methods and findings can be extended to additional languages and national contexts. In addition, future research can examine how the dictionary relates to other phenomena beyond those we studied (e.g., religiosity, foreign policy, and economic investment

Fig. 3. Percentage of threat dictionary terms found in US presidential speeches. The bars represent the average percentages of threat dictionary words found across all speeches and public remarks made by US presidents from 1948 to 2020, with red and blue shading corresponding to each president's political party affiliation (Republican and Democrat, respectively).
among others). In addition, future research that seeks to measure specific types of threat linguistically can apply our measurement development process to create more specialized dictionaries—for instance, on mass shootings or cybersecurity threats.

The threat dictionary may be useful for understanding a number of critical societal issues. History is replete with examples of organizations and political leaders who have been culpable of inflaming threats and peddling fear to obtain popular support or undermine democratic principles (3, 69). The threat dictionary enables comparisons and evaluations of historical and contemporary leaders’ talking points to assess these exaggerations of threats or strategic fabrications of collective dangers and their consequences. This linguistic tool can also be used to examine how threat—whether real or manipulated—propagates across social media and its negative effects online and ultimately, offline. Indeed, on social media platforms, millions of users and news outlets are jockeying to be heard and seen. We have shown how the prevalence of threatening language within tweets increases their widespread dissemination capabilities. While the paper only tested its contagious properties with Twitter behavior during the COVID-19 pandemic, future directions include generalizing these findings to other collective threats. Excessive use of threat words may also explain the disconcerting popularity of counterproductive online content. For instance, an analysis of online groups that capitalize on threat-fueled chatter can reveal which networks are prone to threat-related words is informative not only of people’s daily exposure to epidemic threat, but also of the linguistic footprints that make interesting societal patterns across history visible.

Data Availability. Code and data for these results are available at the Open Science Framework (OSF; https://osf.io/eydqb/). All other data are included in the paper.

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