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ASSESSING SENTIMENT IN CONFLICT ZONES THROUGH SOCIAL MEDIA

by

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While it is widely accepted that polling can assess levels of popular support in a geographic area by surveying a cross-segment of its population, it is less well accepted that analysts can use social media analysis to assess sentiment or popular support within the same space. We examine this question by comparing geographically anchored polling and social media data, utilizing over 1.4 million geo-referenced messages sent through the Twitter network from Yemen over the period from October 2013 to January 2014, to assess both support for extremist groups and support to the Yemeni government. From our research, we conclude that social media data, when combined with polling, has a positive impact on analysis. It can also be a reliable source of stand-alone data for evaluating popular support under certain conditions. Therefore, we recommend future research projects focus on improving the quality of social media data and on operational changes to improve the integration of social media analysis into assessment plans.

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ASSESSING SENTIMENT IN CONFLICT ZONES THROUGH SOCIAL MEDIA

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While it is widely accepted that polling can assess levels of popular support in a geographic area by surveying a cross-segment of its population, it is less well accepted that analysts can use social media analysis to assess sentiment or popular support within the same space. We examine this question by comparing geographically anchored polling and social media data, utilizing over 1.4 million geo-referenced messages sent through the Twitter network from Yemen over the period from October 2013 to January 2014, to assess both support for extremist groups and support to the Yemeni government. From our research, we conclude that social media data, when combined with polling, has a positive impact on analysis. It can also be a reliable source of stand-alone data for evaluating popular support under certain conditions. Therefore, we recommend future research projects focus on improving the quality of social media data and on operational changes to improve the integration of social media analysis into assessment plans.

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LIST OF ACRONYMS AND ABBREVIATIONS

AIC	Akaike information criterion
AFINN	Lexicon developed by Finn Årup Nielsen
AQ	Al-Qaeda
AQAP	Al-Qaeda in the Arabian Peninsula
AQY	Al-Qaeda in Yemen
COIN	Counterinsurgency
CPU	central processing unit
DV	Dependent variable
EU	European Union
GLM	generalized linear model
GRAP	Global Research and Assessment Program
MAUP	modifiable areal unit problem
NDC	National Dialogue Conference
NLP	natural language processing
PII	personally identifiable information
PSYOP	Psychological Operations
SNA	social network analysis
VEO	violent extremist organization
U.S.	United States
USG	United States Government
USSOCOM	United States Special Operations Command
VEO	violent extremist organization

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I. INTRODUCTION

Since nations have existed, they have faced population-centric forms of warfare—rebellion, insurgency, and civil war—in which insurgents typically battle entrenched governments for the loyalty of the populace, with each side's movements and intentions obscured by the fog of conflict. In the modern era, governments rely on laborious, time-consuming, and expensive opinion polls to navigate through this fog. Opinion polls are like green and red marker buoys in a channel, spaced intermittently along the way to help captains determine their positions. Like buoys, polling is reliable and sheds light on known positions in time, but polls are inherently spaced apart from one another and thus lack timeliness. In a sea covered by a thick blanket of fog, buoys can easily be obscured. Like captains navigating in unclear conditions, military commanders navigating through the fog of conflict require timely location information, or else their efforts may founder.

Our research attempts to determine whether social media data analysis can serve as a proxy for or fill in the gap between opinion polls. If so, military commanders could continuously monitor population sentiment and determine whether their efforts were affecting the population.

To answer our questions, we developed a method that reliably measures the geographic distribution of aggregate popular sentiments using data derived from public messages sent through the Twitter network. We then compared these measurements to the spatial distribution of sentiments derived from existing public opinion polls collected during the same period.

For robustness, we tested our approach in Yemen, a difficult test country. Compared to Western countries, Yemen has low levels of Internet access and social media users. The country is also beset by low levels of governance and violent extremist organizations battling for the loyalty of the populace. Yemen is typical of a country that the U.S. military would be tasked to deal with because it is a breeding ground for terrorism.

In total, the data used to develop our new metrics consisted of over 1.4 million tweets, observed in Yemen over the period October 2013 to January 2014. From our research we conclude that social media data, when combined with traditional polling approaches, can greatly improve our situational awareness over what can be learned from polling alone. Under some circumstances, it may be possible to use social media data as a stand-alone tool for evaluating negative sentiment for a standing government or violent extremist organizations vying for control of a country. However, we also find that our method performed better at identifying geographic patterns of negative feelings versus positive feelings regarding the government of Yemen and violent extremist organizations.

We recommend further research focus on improving the algorithm that we developed. Specifically, we recommend testing different timeframes in Yemen, different countries, and Western countries. Finally, we recommend military commanders make greater efforts to combine the use of social media data and more traditional polling approaches. Doing so will allow commanders to better focus counterinsurgency operations on the disaffected portions of the population where partnerships are most critical.

II. LITERATURE REVIEW

A. MILITARY DOCTRINE AND ASSESSMENT

This project was inspired in large part by the team's combined 50 years of service in both the U.S. Navy and U.S. Army, working against asymmetric actors. Our experience waging counterinsurgency operations across the globe has taught us that sentiment is fundamental in gauging success in the type of warfare the U.S. has been focused on for decades.[1] Regrettably, we have watched numerous Special Forces commanders struggle to evaluate the strategic effectiveness of their counterinsurgency operations. We feel this is mainly because they did not have enough information on the populace in the regions where they held responsibility. Compounding this issue is the fact that U.S. Joint Doctrine Publications instruct commanders to measure the effectiveness of their operations as part of a feedback loop, but fail to provide clear ideas of how to do the job or resources to help.[2]

A portion of the doctrine issue we illuminate may be due to the disagreement regarding whether to measure sentiment in the first place. Some would argue there is no difference between conventional military Clausewitzian force-on-force conflicts and a "people's war" (e.g., low-intensity conflict, hybrid warfare, irregular warfare, etc.).[3][4] Therefore, the military should focus simply on the enemy, making popular support irrelevant.[5] Other scholars and theorists, such as counterinsurgency warfare experts, would argue that only the actor who wins *and maintains popular support* will achieve his

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[1] Seth G. Jones, *RAND Counterinsurgency Study,* vol. 4, *Counterinsurgency in Afghanistan* (Santa Monica, CA: RAND Corporation, 2008), 7.

[2] Jack D. Kem, "Assessment: Measures of Performance and Measures of Effectiveness," *Military Intelligence Professional Bulletin* 35, no. 2 (2009): 48–50.

[3] Stuart Kinross, "Clausewitz and Low-Intensity Conflict," *Journal of Strategic Studies* 27, no. 1 (2004): 35–58; Frank Hoffman, "Hybrid Warfare and Challenges," *JFQ* 52, no. 1 (2009); James Clancy and Chuck Crossett, "Measuring Effectiveness in Irregular Warfare," *Parameters* 37, no. 2 (2007): 88.

[4] Clausewitz also spoke about the "passions of the people." The passions of the people were a key part of his trinity of war.

[5] Raphael Cohen, "Just How Important Are 'Hearts and Minds' Anyway? Counterinsurgency Goes to the Polls," *Journal of Strategic Studies* 37, no. 4 (June/July 2014): 609–636; Russell Weigley, *The American Way of War: A History of United States Military Strategy and Policy* (Bloomington, IN: Indiana University Press, 1977).

or her objectives. This is believed because, in Roger Trinquier's words, "the ability to exercise power over a populace depends on the tacit or explicit agreement of the population and in worst-case scenarios on their submission."[6]

Moreover, among those who do not question the relevance of population-centric counterinsurgency warfare, there is disagreement about whether to study quantifiable metrics or qualitative "hearts and minds" metrics, similar to the broader divisions found across the social sciences.[7]

Military units that value behavior-based metrics, such as Psychological Operations, have developed an approach called effects-based operations, which focuses on observable behavior-based metrics to assess military effectiveness.[8] They analyze variables like security, economic indicators, justice indicators, and governance indicators.[9] To do so, they gather and assess public attitudes, beliefs, atmospherics, and opinions via three means: mass-media analysis, open-source analysis, and opinion polling. Passive observation of a local population and mass-media open-source analysis (one-to-many communication modes) provide qualitative insight regarding the attitudes, beliefs, and opinions of key demographics and elites respectively.[10]

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[6] George Casey Jr. et al., *Assessing War: The Challenge of Measuring Success and Failure* (Washington, DC: Georgetown University Press, 2015), 218.

[7] Robert B. Sotire, *Measuring Performance and Effectiveness in Irregular Warfare: Preventing Dysfunctional Behavior* (Newport, RI: Naval War College, 2009).

[8] Edward Smith, "Effects-Based Operations," in *Applying Network-Centric Warfare in Peace, Crisis and War* (Washington, DC: DOD CCRP, 2002).

[9] Jason Campbell and Jeremy Shapiro, "Afghanistan Index: Tracking Variables of Reconstruction and Security in Post-9/11 Afghanistan," Brookings Institution, October 28, 2008, 4–49; Ethan B. Kapstein, "Measuring Progress in Modern Warfare," *Survival* 54, no. 1 (03/01, 2012): 137–158; M. Treblicock and R. Daniels, *Rule of Law Reform and Development: Charting the Fragile Path of Progress* (Surrey, UK: Edward Elgar Publishing, 2008), 42; Craig Cohen, "Measuring Progress in Stabilization and Reconstruction," United States Institute of Peace: Stabilization and Reconstruction Series (2003): 1–12; Michael Dziedzic, Barbara Sotirin, and John Agoglia, eds., "Measuring Progress in Conflict Environments (MPICE)," United States Institute of Peace, March 19, 2008.

[10] Michael T. Flynn, Matthew F. Pottinger, and Paul D. Batchelor, *Fixing Intel: A Blueprint for Making Intelligence Relevant in Afghanistan* (Washington, DC: Center for a New American Security, 2010). doi:ADA511613; John Urry, *Mobilities* (Cambridge, UK: Polity, 2007); Robert Steele, "Open Source Intelligence," in *Handbook of Intelligence Studies,* edited by Loch K. Johnson (Oxford, UK: Routledge, 2007), 129–147.

Proponents of effects-based operations assess support to military operations through behavior-based indicators. This approach is commonly called "hearts and minds," because it measures attitudes, beliefs, and opinions.[11] However, critics of effects-based operations point out questionable relationships between observable behavior and popular support indicators.[12]

B. SOCIAL MEDIA ANALYSIS

An alternative approach to assessment, not considered within doctrines, may be provided through social media analysis. Social scientists now have access to massive quantities of data sourced through public Internet and social media sites. The techniques used to comb through the hard drives packed with data have various titles, which can be organized under the broad heading of *data mining*.[13] In general terms, data mining is a process of description and prediction that allows analysts to sort, analyze, and visualize data.[14] One area of knowledge that builds from data mining is deriving meaning from written text. This has been called *sentiment analysis*, *opinion mining*, and *subjectivity analysis*.[15] We refer to Georgios Paltoglou, a senior lecturer from the University of Wolverhampton, United Kingdom, who defines it as follows:

> Specifically, opinion mining addresses the problem of detecting, extracting, analyzing, and quantifying expressions of private states in written text in an automatic, computer-mediated fashion. Particular emphasis should be placed on the term "computer-mediated," as the field

[11] David Galula, *Counterinsurgency Warfare: Theory and Practice* (Greenwood Publishing Group, 2006); United States Joint Chiefs of Staff, *Joint Publication Counterinsurgency* (JP 3–24) (Washington, DC: U.S. Government Printing Office, 2013); Jordan Stern, *Civil Military Operations and Military Information Support Operations Coordination: A Non-Kinetic Ballast for Disciplined Counterinsurgency Operations* (Bethseda, MD: Small Wars Foundation, 2011).

[12] Christopher Paul and William Marcellino, "Dominating Duffer's Domain: Lessons for the 21st-Century Information Operations Practitioner," RAND Corporation, Santa Monica: CA, 2016.

[13] Usama Fayyad, Gregory Piatetsky-Shapiro, and Padhraic Smyth, "From Data Mining to Knowledge Discovery in Databases." *AI Magazine* 17, no. 3 (1996): 37.

[14] Alexander Furnas, "Everything You Wanted to Know about Data Mining but Were Afraid to Ask," *Atlantic,* April 3, 2012.

[15] Bo Pang and Lillian Lee. "Opinion Mining and Sentiment Analysis," *Foundations and Trends in Information Retrieval* 2, no. 1–2 (2008): 1–135.

has a particular focus on designing, analyzing, and implementing software that performs the aforementioned analysis in an automatic manner.[16]

There are many social media sources for data mining, including social networking (e.g., Facebook), bookmarking (e.g., Pinterest), social news (e.g., Reddit), media sharing (e.g., YouTube), microblogging (e.g., Twitter), and various blogs/forums.[17] Researchers from numerous fields are looking deeper into questions using big data from social media to study behavior in humans, politics, financial markets, and public opinion, and movement patterns of groups to identify the spread of diseases, migration patterns of animals, patterns of behavior in humans, and cross-border routes (e.g., smuggling

[16] Georgios Paltoglou, "Sentiment Analysis in Social Media," in *Online Collective Action, Dynamics of the Crowd in Social Media,* eds. N. Agarwal, M. Lim, and R. T. Wigard (Vienna, Austria: Springer International Publishing, 2013), 3–17.

[17] Alexander Pak and Patrick Paroubek. "Twitter as a Corpus for Sentiment Analysis and Opinion Mining," in *Proceedings of the Seventh Conference on International Language Resources and Evaluation (LREC '10),* eds. Nicoletta Calzolari et al (Valletta, Malta: European Language Resources Distribution Agency, May 2010); Fayyad, Piatetsky-Shapiro, and Smyth, "From Data Mining to Knowledge Discovery"; Stefan Stieglitz and Linh Dang-Xuan, "Political Communication and Influence through Microblogging: An Empirical Analysis of Sentiment in Twitter Messages and Retweet Behavior," in *Proceedings of the 45th Hawaii International Conference on System Science,* ed. Ralph H. Sprague Jr. (Washington, DC: IEEE Computer Society, 2012), 3500–3509; Mike Thelwall, Kevan Buckley, and Georgios Paltoglou, "Sentiment in Twitter Events," *Journal of the American Society for Information Science and Technology* 62, no. 2 (2011): 406–418; Xiaofeng Wang, Matthew S. Gerber, and Donald E. Brown, "Automatic Crime Prediction Using Events Extracted from Twitter Posts," in *SBP'12 Proceedings of the 5th International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction*, eds. Shanchieh Jay Yang, Ariel M. Greenberg, and Mica Endsley (Berlin, Germany: Springer-Verlag Berlin, Heidelberg, 2012), 231–238.

routes).[18] Other areas of research include the relationship between social media and individual or group behavior, which can potentially assess the impact of online activism or a government's public relations campaign.[19] There are also efforts to understand social mobilization and collective violence, of particular value in assessing a population through social movement theory.[20] However, many of these studies have faced substantial barriers. For instance, most studies focus on Western countries that use the English language and are dominated by Western culture.[21]

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18 Morgan R. Frank et al., "Happiness and the Patterns of Life: A Study of Geolocated Tweets," *Scientific Reports* 3 (2013); Bartosz Hawelka et al., "Geo-Located Twitter as Proxy for Global Mobility Patterns," *Cartography and Geographic Information Science* 41, no. 3 (2014): 260–271; Marcel Salathé et al., "Influenza A (H7N9) and the Importance of Digital Epidemiology," *New England Journal of Medicine* 369, no. 5 (Aug 1, 2013): 401–4; Justine I. Blanford et al., "Geo-Located Tweets: Enhancing Mobility Maps and Capturing Cross-Border Movement," *PloS ONE* 10, no. 6 (Jun 2015, 2015); Zhiyuan Cheng, James Caverlee, and Kyumin Lee, "You Are Where You Tweet: A Content-Based Approach to Geo-Locating Twitter Users," in *Proceedings of the 19th ACM International Conference on Information and Knowledge Management*, 2010, 759–768; Ryan Compton, David Jurgens, and David Allen, "Geotagging One Hundred Million Twitter Accounts with Total Variation Minimization," *Big Data (Big Data), 2014 IEEE International Conference on,* 2014, 393–401; Michael D. Conover et al., "The Geospatial Characteristics of a Social Movement Communication Network," *PloS ONE* 8, no. 3 (2013): e55957; Andreas Kaltenbrunner et al., "Far from the Eyes, Close on the Web: Impact of Geographic Distance on Online Social Interactions," *Proceedings of the 2012 ACM Workshop on Online Social Networks* (New York: ACM, 2012), 19–24; Juhi Kulshrestha et al., "Geographic Dissection of the Twitter Network," *ICWSM*, 2012; Ryong Lee and Kazutoshi Sumiya, "Measuring Geographical Regularities of Crowd Behaviors for Twitter-Based Geo-Social Event Detection," in *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location-Based Social Networks* (New York: ACM, 2010), 1–10; Kalev Leetaru et al., "Mapping the Global Twitter Heartbeat: The Geography of Twitter," *First Monday* 18, no. 5 (2013); Lewis Mitchell et al., "The Geography of Happiness: Connecting Twitter Sentiment and Expression, Demographics, and Objective Characteristics of Place," *PloS ONE* 8, no. 5 (2013): e64417; Stephen C. Nemeth, Jacob A. Mauslein, and Craig Stapley, "The Primacy of the Local: Identifying Terrorist Hot Spots Using Geographic Information Systems," *Journal of Politics* 76, no. 2 (2014): 304–317; Yuri Takhteyev, Anatoliy Gruzd, and Barry Wellman, "Geography of Twitter Networks," *Social Networks* 34, no. 1 (2012): 73–81; Quan Yuan et al., "Who, Where, When and What: Discover Spatio-Temporal Topics for Twitter Users," in *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, eds. Ingerjit S. Dhillon et al. (New York: ACM, 2013), 605–613.

19 Raz Schwartz and Germaine R. Halegoua, "The Spatial Self: Location-Based Identity Performance on Social Media," *New Media & Society,* April 9, 2014, 1–18. doi:10.1177/1461444814531364.

20 Doowan Lee, "A Social Movement Approach to Unconventional Warfare," *Special Warfare* July-September, Volume 26, no. Issue 3 (2013), 27-32.; Doug McAdam, *Political Process and the Development of Black Insurgency, 1930-1970*, ed. 2ndUniversity of Chicago Press, LTD., London, 1982).

21 T. Camber Warren, "Mapping the Rhetoric of Violence: Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media," prepared for presentation at the Annual Meeting of the American Political Science Association, Sept. 3–6, 2015, San Francisco, CA.

Nevertheless, large strides have been made in analyzing individual messages to determine underlying sentiment, which is the focus of our research.[22] These strides in sentiment studies have resulted in new approaches, including natural language processing, text analysis, linguistic inquiry, word count, keyword spotting, lexical affinity, statistical methods, and concept-level techniques.[23] Keyword spotting is the most simplistic approach, because it sorts text by category using unambiguous emotional words.[24] For example, if keyword software is programmed to look for the word *government*, this is because the word government has already been associated with an emotional category like good or bad. Another approach is lexical affinity, which sorts text much the same way as keyword spotting. The big difference is that it is able to

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22 Ahmed Abbasi, Hsinchun Chen, and Arab Salem, "Sentiment Analysis in Multiple Languages: Feature Selection for Opinion Classification in Web Forums," *ACM Transactions on Information Systems (TOIS)* 26, no. 3 (2008): 12; Apoorv Agarwal et al., "Sentiment Analysis of Twitter Data," in *Proceedings of the Workshop on Languages in Social Media*, eds. Meena Nagarajan and Michael Gamon, Association for Computational Linguistics, 2011, 30–38; Younggue Bae and Hongchul Lee, "Sentiment Analysis of Twitter Audiences: Measuring the Positive or Negative Influence of Popular Twitterers," *Journal of the American Society for Information Science and Technology* 63, no. 12 (2012): 2521–2535; Albert Bifet and Eibe Frank, "Sentiment Knowledge Discovery in Twitter Streaming Data," in *DS'10 Proceedings of the 13th International Conference on Discovery Science*, eds. Berharnd Pfahringer, Geoff Holmes, and Achim Hoffmann (Heidelberg, Germany: Springer-Verlag, 2010), 1–15; Johan Bollen, Alberto Pepe, and Huina Mao, "Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena," in *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media (ICWSM 2011),* eds. N. Nicolov and J. G. Shanahan (Barcelona, Spain: AAAI Press, July 2011), 1–10; Peter Sheridan Dodds et al., "Temporal Patterns of Happiness and Information in a Global Social Network: Hedonometrics and Twitter," *PloS ONE* 6, no. 12 (2011): e26752; Rui Fan et al., "Anger Is More Influential than Joy: Sentiment Correlation in Weibo." *PloS ONE* 9, no. 10 (2014): e110184; M. Ghiassi, J. Skinner, and D. Zimbra, "Twitter Brand Sentiment Analysis: A Hybrid System Using N-Gram Analysis and Dynamic Artificial Neural Network," *Expert Systems with Applications* 40, no. 16 (2013): 6266–6282; Scott A Golder and Michael W. Macy. "Diurnal and Seasonal Mood Vary with Work, Sleep, and Daylength across Diverse Cultures," *Science* 333, no. 6051 (2011): 1878–1881; Shu Huang et al., "Sentiment and Topic Analysis on Social Media: A Multi-Task Multi-Label Classification Approach," in *Proceedings of the 5th Annual ACM Web Science Conference* (New York: ACM, 2013), 172–181; Long Jiang et al., "Target-Dependent Twitter Sentiment Classification," in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies,* vol. 1 (Stroudsburg, PA: Association for Computational Linguistics, 2011), 151–160; Lewis Mitchell et al., "The Geography of Happiness"; Brendan O'Connor et al., "From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series," in *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*, 2010, 1–2.

23 Erik Cambria et al., "New Avenues in Opinion Mining and Sentiment Analysis," IEEE Intelligent Systems no. 2 (2013): 15–21; Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan, "Thumbs Up? Sentiment Classification Using Machine Learning Techniques," in Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing (Stroudsburg, PA: Association for Computational Linguistics, 2002); Namrata Godbole, Manja Srinivasaiah, and Steven Skiena, "Large-Scale Sentiment Analysis for News and Blogs," Icwsm 7, no. 21 (2007): 219–222.

24 Andrew Ortony, Gerald L. Clore, and Allan Collins, *The Cognitive Structure of Emotions* (New York: Cambridge University Press, 1990).

measure the distance between words in a text string and assign an intensity value based on the distance.[25]

The statistical method is slightly more complex. It uses natural language processing (NLP) to cull through massive amounts of data and assigns values to patterns in the text. One example is the "bag of words" approach, which analyzes a text without considering the order or distance between words. This approach essentially counts the frequency of words co-occurrences, and then infers "negative" or "positive" valence categories based upon the patterns of these co-occurrences. It is commonly used to filter spam by using a list of valued words to determine whether an email is an advertisement (i.e., negative words) or a legitimate communication (i.e., positive words).[26]

The most complex approaches are known as concept-level techniques. These techniques primarily focus on semantic analysis of the text. This means that they evaluate how concepts in one text relate to concepts in another text.[27] This form of social media analysis, rooted in lexical analysis, examines the content of messages.[28] Lexical analysis's subfields and analytical methods include discourse analysis, narrative analysis, trend analysis, and sentiment analysis. Discourse analysis reviews both two-way conversations and one-way rhetoric. These inputs typically flow from an organization's spokesperson or a key communicator to his or her listeners, readers, or viewers.[29] Narrative analysis highlights how an individual or group reflects their understanding of their place in the world; this approach is increasingly applied within the field of social

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[25] Hugo Liu, Henry Lieberman, and Ted Selker, "A Model of Textual Affect Sensing Using Real-World Knowledge," in *Proceedings of the 2003 International Conference on Intelligent User Interfaces* (New York: ACM, 2003).

[26] Peter Turney, "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews," in *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics* (Stroudsburg, PA: Association for Computational Linguistics, 2002), 417–424.

[27] Erik Cambria et al., "Sentic Patterns: Dependency-Based Rules for Concept-Level Sentiment Analysis," *Knowledge-Based Systems* 69, (2014): 45–63.

[28] Pang and Lee, "Opinion Mining and Sentiment Analysis."

[29] Teun A. van Dijk, "Critical Discourse Analysis," in *The Handbook of Discourse Analysis,* eds. Deborah Schiffrin, Deborah Tannen, and Heidi E. Hamilton (Malden, Massachusetts: Blackwell Publishers, 2001, 349–371.

movement theory.[30] Trend analysis instead focuses on temporal patterns in discourse, mathematically identifies items experiencing accelerating increases in frequency, whether those items are word and phrases used in search engines, or 'trending' stories on news sites.[31]

The output of sentiment analysis can take multiple forms: including ordered, continuous, and categorical values. Ordered outputs might be either positive or negative, or might include a ternary division between positive, negative, and neutral.[32] Categorical values are similar, but they assign no actual numerical content, so the categories are just boxes like "a" or "cat," which do not imply that one value is numerically greater than another.

Researchers have used numerous methods to analyze and visually represent social media data. Geospatial analysis, for instance, is a visual representation of data that looks at identifying spatially related patterns between events and/or individuals and their locations.[33] A great example of this approach is heat maps. A heat map is a graphical representation of data in which the individual values in a matrix are represented as colors. The color coding highlights distinctions between values taken by variables in a hierarchy.

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[30] Catherine K. Riessman, "Narrative Analysis," in M.S. Lewis-Beck, A. Bryman, and T. Futing Liao, eds., *SAGE Encyclopedia of Social Science Research Methods*, vol. 3 (Thousand Oaks, CA: SAGE Publications, 2003); Arthur A. Berger, *Media Analysis Techniques* (Thousand Oaks, CA: SAGE Publications, 2013); Ruth E. Page, *Stories and Social Media: Identities and Interaction* (Oxford, UK: Routledge, 2013).

[31] Jey H. Lau, Nigel Collier, and Timothy Baldwin. "On-Line Trend Analysis with Topic Models: #Twitter Trends Detection Topic Model Online," conference paper, *Proceedings of COLING* 2012, December 2012; M. Osborne et al., "Bieber No More: First Story Detection Using Twitter and *Wikipedia*," in *SIGIR 2012 Workshop on Time-Aware Information Access* Oregon, 2012; S. Petrovic, M. Osborne, and V. Lavrenko, "Streaming First Story Detection with Application to Twitter," in *Proceedings of Human Language Technologies: The 11th Annual Conference of the North American Chapter of the Association for Computational Linguistics (NAACL HLT 2010)* (Stroudsburg, PA: Association for Computational Linguistics: 2010), 181–189.

[32] Anna Chmiel et al., "Negative Emotions Boost User Activity at BBC Forum," *Physica A: Statistical Mechanics and Its Applications* 390, no. 16 (2011): 2936–2944; Marija Mitrović, Georgios Paltoglou, and Bosiljka Tadić, "Quantitative Analysis of Bloggers' Collective Behavior Powered by Emotions," *Journal of Statistical Mechanics: Theory and Experiment* 2011, no. 02 (2011): P02005.

[33] Anthony Stefanidis, Andrew Crooks, and Jacek Radzikowski, "Harvesting Ambient Geospatial Information from Social Media Feeds," *Geojournal* 78, no. 2 (2013): 319–338; Daniel Sui and Michael Goodchild, "The Convergence of GIS and Social Media: Challenges for GIScience," *International Journal of Geographical Information Science* 25, no. 11 (2011): 1737–1748; Sarah Elwood, Michael F. Goodchild, and Daniel Z. Sui, "Researching Volunteered Geographic Information: Spatial Data, Geographic Research, and New Social Practice," *Annals of the Association of American Geographers* 102, no. 3 (2012): 571–590.

Social network analysis (SNA), on the other hand, uses social media data to identify the ties between actors and the strengths of those ties.[34] The ties are frequently displayed in a hub-and-spoke wheel of actors and their connections to other actors in a network.

A variety of issues arise when attempting to determine sentiment using the Internet and social media, including the source, sample representation, and language. It is important to note that data derived from these sources often do not represent proper "samples" in the statistical sense.[35] Source issues involve not knowing where the data originates from. Imagine a pollster asking questions of a person who is standing behind a white sheet. The pollster cannot know for certain the identity of the source. Data found online may have all kinds of unwanted sources including bots, Internet agents, wanderers, brokers, trolls, propagandists, and even official news outlets that can skew the results.[36] Additionally, in demographic terms, "Internet and social media users are not likely a true representation of a given population," and as a result they do not necessarily provide a representative sample for analysis.[37] For instance, access to the Internet in many countries may only be found in urban areas with improved infrastructure. People from rural, less connected areas may therefore be underrepresented. Other demographic issues related to Internet and social media access includes age, education, gender, and income. Still, there are widely accepted statistical techniques for dealing with such issues. As we explain more fully, it may be possible reduce such difficulties by using 'control variables' to hold certain factors constant when examining the effects of a variable of interest.

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[34] Sean F. Everton, *Disrupting Dark Networks*, vol. 34 (New York: Cambridge University Press, 2012); Stuart Koschade, "A Social Network Analysis of Jemaah Islamiyah: The Applications to Counterterrorism and Intelligence," *Studies in Conflict & Terrorism* 29, no. 6 (2006): 559–575; Stanley Wasserman and Katherine Faust, *Social Network Analysis: Methods and Applications*, vol. 8 (New York: Cambridge University Press, 1994).

[35] Stephen Ansolabehere and Eitan Hersh, "Validation: What Big Data Reveal about Survey Misreporting and the Real Electorate," *Political Analysis* (2012): mps023; Pablo Barberá, "How Social Media Reduces Mass Political Polarization: Evidence from Germany, Spain, and the US," working paper prepared for the 2015 APSA Conference, New York University, 2014; Alan Mislove et al., "Understanding the Demographics of Twitter Users," *ICWSM* 11 (2011): 5.

[36] Fah-Chun Cheong, *Internet Agents: Spiders, Wanderers, Brokers, and Bots* (San Francisco, CA: New Riders Publishing, 1996).

[37] Ansolabehere and Hersh, "Validation: What Big Data Reveal"; Pablo Barberá and Gonzalo Rivero, "Understanding the Political Representativeness of Twitter Users," *Social Science Computer Review* 33, no. 6 (December 1, 2015): 712–729; Mislove et al., "Understanding the Demographics of Twitter Users."

Since most social networking platforms were built by English speakers, the diversity of written formats seen in other languages can pose its own challenges. Processing English text is relatively easy compared to processing text in some foreign languages. English uses a relatively simple alphabet that contains separate letters for consonants and vowels. Other writing forms, for instance Chinese logograms, are built of glyphs that represent words. A glyph is a meaningful component of a word, rather than a phonetic element. Ideographic writing is based on pictures that represent concepts or ideas, rather than specific words. In contrast, a segmental script, like Arabic, uses graphemes that represent phonemes, distinct units of sound that distinguish one word from another.[38]

Given these difficulties, one approach, taken by many existing works, is to stick with English-language databases. However, when faced with a research question that requires analysis of foreign societies, such an approach seems too sharply limiting. Promisingly, recent advances in machine translation have increased the ease of generating relatively reliable translations of single words and short phrases.[39] For instance, researchers can access automated machine-generated translations through online tools, such as the Google Translate API. This service allows for simple translation from a wide variety of languages to other languages. More nuanced approaches to machine translation utilize natural language parsers to consider the broader grammatical structures of sentences and paragraphs. However, this requires careful tokenization of the text combined with language-specific grammar rules, which can make this approach cost-prohibitive in computational terms when face with very large textual corpora.

[38] Michael A. Halliday, *Spoken and Written Language* (Oxford, UK: Oxford University Press, 1989).

[39] Mohammad Salameh, Saif M. Mohammad, and Svetlana Kiritchenko, "Sentiment after Translation: A Case-Study on Arabic Social Media Posts," in *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (2015): 767–777.

III. BACKGROUND—YEMEN

Yemen is an ideal place to test our research. Compared to Western countries, Yemen has low levels of Internet access and few social media users. The country is also struggling with low levels of governance and violent extremist organizations battling for the loyalty of the populace. Yemen is typical of a country that the U.S. military would be tasked to deal with, because it is a breeding ground for terrorism. The following section delves into the problems facing Yemen.

For the majority of the 20th century, Yemen was divided between the Ottoman and British empires. Following the fall of the Ottoman Empire, northern Yemen became the Yemen Arab Republic. Southern Yemen (People's Democratic Republic of Yemen) remained a British colony until 1967. Finally, in 1990, northern and southern Yemen united. Four years after becoming a united nation, Yemen experienced a two-month-long civil war over governance.

Since the 1994 civil war, Yemen has become increasingly unstable. Violent extremist organizations have filled gaps where the government has failed. According to the Fund for Peace, the country was ranked in the top 10 most fragile in both 2013 and 2014.[40] Numerous organizations are vying for control of the weak Yemeni government.

A. VIOLENT EXTREMIST ORGANIZATIONS

Violent extremist organizations (VEO) in Yemen include the Shia Houthis, Sunni Salafi, and al-Qaeda in the Arabian Peninsula (AQAP). All three VEOs have challenged the government over control of territory, threatened government progress initiatives such as the National Dialogue Conference (NDC), conducted kidnapped for ransom, murdered civilians, and leveraged poor socioeconomic conditions and government corruption, leaving Yemen unstable and a security concern for the rest of the world and organizations that want to help. Non-governmental agencies are loath to help for fear of their safety on the ground. For example, on November 14, 2013, VEOs sabotaged the Internet and cell

[40] Fund for Peace, "The Fragile States Index 2015," accessed June 15, 2016, http://fsi.fundforpeace.org/rankings-2014.

phone towers in the Shabwa Governorate.[41] The Yemeni population suffered as a result, and the government's response was popularly viewed as insufficient. The government claimed many excuses for their lack of action, including insufficient resources, security concerns, and roads barricaded by the VEOs. Ultimately, the government missed the opportunity to exploit VEO violent actions via propaganda or other mean, leaving the VEOs impervious to public scrutiny, despite their attacks on public infrastructure.

B. HOUTHIS

The Shia Houthis believe they are direct descendants of the Prophet Muhammad, making them the lawful rulers of Yemen.[42] Needless to say, this places them at odds with the government. Because of their violent actions, they are deemed insurgents. Compounding the discontent stemming from the Houthis' religious justification, the government has intentionally marginalized the group, placing them at odds with the rest of society and reducing their socioeconomic significance. Marginalization of the Houthis began with Saleh, president of Yemen from 1990 to 2012, and is believed to be the foundation for the 2004 Yemen civil war.[43]

Saudi Arabia has generally viewed the Houthis as a threat and readily agreed to the Yemeni government's request to bomb the Houthis' home territory along the Saudi border in November 2009. Additionally, Saudi Arabia is claimed to have contributed between $200 and $300 million annually in security assistance to President Saleh.[44] Saudi Arabia was also involved in exerting Wahhabi influence in Yemen and most recently in the northern Sa'ada Governorate.[45] The Houthis remain wary of attacks from Saudi Arabia and the Yemeni Army.

[41] Ibid.

[42] U.S. Government, U.S. Military, and Department of Defense, *Yemen in Perspective – Orientation Guide and Yemeni Cultural Orientation: Geography, History, Economy, Security, Customs, Aden, Sanaa, Sunni, and Shi'a, Sufism, Qat Chewing, Al-Qaeda, Houthi Rebellion* (Cleveland, OH: Progressive Management, 2015), 1-658, Kindle edition.

[43] Ibid.

[44] Ibid.

[45] Ibid.

Iran, on the other hand, generally views the Houthis as useful proxies against the Saudis. Interestingly, Iran and the Houthis do not follow the same Shia ideology. Iran conveniently ignores the fact that the Houthis follow Fiver Shia, which does not acknowledge later imams, while the Iranians believe in Twelver Shia. Despite this religious difference, Iran is suspected of providing financial funding, military training, and material aid to the Houthis via Hezbollah.[46]

C. SALAFIS

Sunni Salafism was established around the middle of the 19th century in Egypt.[47] Salafi Muslims moved to Yemen about three decades ago.[48] They believe in re-establishing ancient traditions of Islam and do not believe in religious innovation.[49] The movement is divided into three categories: those who avoid politics, those who advocate in favor of politics, and those who form small groups of jihadists.[50] Salafism is often associated with Wahhabism, even though the two ideologies are dissimilar.[51]

In the fall of 2011, Salafis began smuggling weapons into the town of Dammaj, despite Houthi requests to stop. This resulted in two years of infighting between Sunni and Shia Muslims in Yemen. The Houthis and Salafis perpetuated the conflict until a presidential committee brokered a ceasefire on January 11, 2014. Part of the deal involved the forced relocation of hundreds of non-local Salafi families, in addition to 150,000 refugees from the conflict area.[52]

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[46] U.S. Government, Department of Defense, and U.S. Army, *The Conflicts in Yemen and U.S. National Security – Yemeni Regional Politics and Saudi Arabia, Drones, Qat Chewing, Al-Qaeda, War on Terror, Houthi Tribesmen Rebellion, Zaydi Shiite Sect, Kleptocracy* (Cleveland, OH: Progressive Management, 2014), Kindle edition.

[47] Joseph J. Hobbs, *Fundamentals of World Regional Geography*, ed. 4, (Cengage Learning, 2016), 232.

[48] U.S. Government, Department of Defense, U.S. Army, U.S. Navy, U.S. Marine Corps, Army War College, and U.S. State Department, *2015 Complete Guide to Al-Qaeda in Yemen: Al-Qaida in the Arabian Peninsula (AQAP)* (Cleveland, OH: Progressive Management, 2015), Kindle edition.

[49] "Politics and the Puritanical," *Economist*. June 2015, "http://www.economist.com/news/middle-east-and-africa/21656189-islams-most-conservative-adherents-are-finding-politics-hard-it-beats.

[50] Ibid.

[51] Ibid.

[52] U.S. Government et al., *The Conflicts in Yemen and U.S. National Security*, 232.

D. AL-QAEDA IN THE ARABIAN PENINSULA AND YEMEN

AQAP has systematically built their network in Yemen over time, starting in 2006. By 2009, AQAP was known simply as Al-Qaeda in Yemen (AQY) and had grown strong enough to announce a southern independence movement. Bin Laden noticed that tribal support was imperative, and in 2000 sent messengers to Yemen to win local support through propaganda, welfare programs, and other essential material needed in impoverished villages.[53]

AQY followed a systematic process for every village they entered. They began by announcing their arrival by disseminating propaganda handbills, CDs, and DVDs which contained their *dawa* ideology. Slowly, they set about convincing influence leaders in each village to support them. Once they had influenced a small number of well-respected villagers to vouch for them, they would leave a few fighters behind and move on to the next village.[54] In a relatively short time, they had exponentially increased domestic support of AQY and global support of AQAP.

AQY also used other relatively ingenious methods to expand in Yemen, such as marrying into a given village and planning prison breaks for members who were imprisoned. Ultimately, they took advantage of uneducated, impoverished, and disenfranchised Yeminis villages.[55]

They also had a well-developed communication and marketing strategy that enabled them to build connective insurgent tissue in Yemen and around the globe. Their marketing campaign exponentially increased domestic support of AQY in impoverished and disenfranchised Yemini villages.[56]

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[53] Abdel Bari Atwan, *After Bin Laden: Al-Qaeda, the Next Generation* (London, UK: Saqi Books, London, 2012), 303.

[54] Ibid.

[55] Ibid.

[56] Ibid.

AQY fighters also assisted villagers with basic security. Villagers in the Rada'a district, Al Bayda Governorate, were seeking police or military basic security, which they were not receiving from the national government.[57]

Of course, not everything AQY did was positive. On December 5, 2013, AQY attacked a hospital, leaving over 50 people dead and 215 injured. Seeing the negative reaction, AQY sent an apology to the families of the deceased but stated that though the attack had been an accident, compartments in the building had supported U.S. drone operations.[58]

E. GOVERNMENT OF YEMEN

President Hadi (Yemeni president February 2012–present) has generally been associated with attempts to transform Yemen and heal its deep wounds. His greatest achievement may be the National Dialogue Conference (NDC), which convened in November 2013 and concluded in January 2014. Hadi began the conference by returning land in southern Yemen seized during the civil war.[59] During the conference, he proposed transforming Yemen into a federal system with six regions.[60] Hadi believed having six regions would benefit the southern Yemeni cities, his base of support. This plan did nothing for the opposition, however. Houthis living in the poorest northern mountain region of Yemen would receive minimal financial support and lose their sea access. Not surprisingly, Hadi was unable to gain the support he needed to enact his federation proposal, because the Houthis saw no benefit in it.[61]

In a strategic sense, the NDC was an initiative to bring peace to Yemen, yet it was immediately marked with violence. The conference started with an assassination of a

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57 Ibid.

58 Ibid.

59 Ibid.

60 U.S. Government et al., *2015 Complete Guide to Al-Qaeda in Yemen.*

61 "Yemen Crisis: Who Is Fighting Whom?" BBC News, October 14, 2016, http://www.bbc.com/news/world-middle-east-29319423.

Houthi representative on November 22, 2013.[62] It was extended two weeks past its scheduled conclusion in January because of an impasse and then completely collapsed with the assassination of a second Houthi representative on January 21, 2014.

Internationally, Yemen was having mixed luck, though the country was making progress in some circles. In October 2013, Hadi met with EU leaders from France and Germany who praised the NDC initiative.[63] On the other hand, Transparency International ranked Yemen in the top 10 most corrupt states.[64]

Domestically, the Yemeni government faces serious governance challenges. The government approved drone strikes and army attacks on VEOs, which were likely the cause of the numerous antigovernment protests that followed. Citizens then began demanding human rights after AQY enacted sharia law in several areas they had siezed. Regions and tribes that were unhappy with sharia law went to the NDC to express their views. People unhappy with police corruption protested with slogans such as "Handcuffs Must Break."[65] To make matters worse, Yemen approved several U.S. drones strikes that resulted in collateral damage. The "Red Wedding" was one such drone strike. On December 12, 2013, 15 people were killed on their way to a wedding in Al Bayda. Tragically, the wedding party had been mistaken for an AQAP convoy.[66] Yemen's government also faced issues providing basic necessities such as electricity, low energy and food prices, and security. The International Institute for Strategic Studies Armed Conflict reported on January 6, 2014, that 54% of Yemenis were living in poverty and 40% of Yemenis were unemployed.[67] Roads and travel inside much of the country have been blocked by VEOs.

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[62] International Institute for Strategic Studies, "Yemen (Houthis / AQAP / SMM)," Armed Conflict Database, accessed October 11, 2016, http://acd.iiss.org/en/conflicts/yemen--houthis-aqap-smm-9651?year=2013&month=10.

[63] Ibid.

[64] Transparency International, "Corruption Perceptions Index 2013," accessed June 14, 2016, http://www.transparency.org/cpi2013/results.

[65] Ibid.

[66] Ibid.

[67] International Institute for Strategic Studies, "Yemen (Houthis / AQAP / SMM)," Armed Conflict Database, accessed October 11, 2016, http://acd.iiss.org/en/conflicts/yemen--houthis-aqap-smm-9651?year=2013&month=10

IV. RESEARCH METHODS

A. HYPOTHESIS

We propose that social media analysis can overcome the limitations of traditional collection and assessment methods by assessing a population's attitudes, beliefs, and opinions using social media data and sentiment analysis. If relationship is found via logistical regression analysis, the study may provide scholars, practitioners, and the U.S. military a new method to analyze sentiment in lieu of a traditional survey and a way to assess the full spectrum of government operations and lines of effort in conflict zones. Additionally, future research may provide insight into social network analysis, social movement theory, and communications theory.

B. DATA AND METHODS

1. Social Media

We began our research with an archive of Twitter data that contained three billion messages and 40 terabytes of data in total, licensed by NPS. The archive represented a 10% randomized sample of the total number of tweets that occurred over a 12-month timeframe. Our research analyzed data spanning a four-month timeframe, from October 1, 2013, through January 31, 2014.

Traditional computational approaches search across strings of text in serial order. However, searching 40 terabytes of Twitter traffic using standard computational approaches would be very cumbersome and slow. Our approach instead utilized a highly parallelized in-memory database application developed by Camber Warren to speed the computations.[68] The approach utilizes "swarms" of parallel computational units to operate in tandem. This requires parallel loading of individual CPU cores, allowing it to

[68] T. Camber Warren, "Mapping the Rhetoric of Violence: Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media," prepared for presentation at the Annual Meeting of the American Political Science Association, September 3–6, 2015, San Francisco, CA.

avoid "resource conflicts, without the need for hierarchical control structures," which are a traditional computational bottleneck.[69]

The first task using this approach is to reference each message to a location in time and space. Each tweet contains underlying metadata that identifies the tweet's date time stamp and the user's location. The user location is based on either the user's profile setting for their hometown or, less commonly, geo-tagging on the tweet itself. The location is converted into latitude/longitude, allowing us to match it to other geo-referenced data sources.

2. Sentiment Dictionary

Our next task was to develop the parameters of our message content search, by building a "sentiment dictionary" (sometimes called a "sentiment lexicon"). This is a list of words that are assigned positive, negative, and/or neutral values manually or through natural language processing (NLP). We chose the AFINN dictionary that was developed by Finn Årup Nielsen.[70] One advantage of this particular lexicon is that it explicitly captures intensity, using a scale that ranges from -5 to +5, allowing researchers to eliminate neutral responses and focus on extreme negative or extreme positive responses. We limited our lexicon to words with score magnitudes of at least 3 (positive or negative) in order to reduce neutral responses and limit analysis to the far left and right sides of the response scale.

We also selected concept search terms reflecting key aspects of Yemeni society and politics. First, we sought to capture the concept of *institutional confidence*. The naming convention for search terms associated with government support was designed to include formal and informal ways of referencing government institutions:

1) Yemeni + name of institution/individual (e.g., Yemeni Army, Yemeni Soldiers),

2) our + name of institution/individual (e.g., our government, our president),

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69 Ibid.

70 Finn Årup Nielsen, "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs," *arXiv preprint arXiv: 1103.2903* (2011).

3) my + name of institution/individual (e.g., my city council, my mayor),

4) location + name of institution/individual (e.g., Aden's City Council, Aden's mayor),

5) title + name of senior individual associated with an institution (e.g., President Hadi),

6) name of senior individual associated with an institution without title (e.g., Abdullah Mohsen al-Akwa).

Second, we sought to capture the concept of support for extremism. The naming convention for search terms associated with extremist support included the different ways the organization was identified along with senior leaders within the organization. The names and leaders were derived from government websites and multiple conflict databases. A list of search terms was compiled to separately assess each of the 10 institutions and the violent extremist organizations evaluated in the survey. The combination of all terms associated with the government comprised the search criteria for institution. All terms associated with VEOs, along with specific terms related to jihad and sharia, comprised the search criteria for extremism.[71]

Both the sentiment dictionary and concept dictionary were then translated from English to Arabic using the automated Google Translate API. In an attempt to address the impact of translation potentially switching a word's sentiment, we also translated each word back into English and replaced words that no longer matched their originals with manually selected words from Google Translate or else deleted them. We checked the Google Translate results with two humans. The first was Major Joshua Wines, and the second was a native Arabic speaker who teaches Arabic at the U.S. Defense Language Institute in Monterey, California.

3. Kernel Density Estimates

Traditional spatial regression techniques entail selecting a political boundary like a city, county, or state, as the unit of analysis. However, such approaches are subject to a

[71] Concept dictionary is in attached Appendix: Concept Dictionary.

statistical bias called the modifiable areal unit problem (MAUP),[72] which renders such estimates highly unreliable. In contrast, the approach taken here seeks to convert the metrics derived from social media messages into continuous spatial surfaces. For each concept and for each month in our study period, we estimated a continuous spatial surface, representing the relative density of messages referencing a concept in a particular place and time. We smoothed the results using two-dimensional binned Gaussian kernel density interpolation.[73] To avoid arbitrary limitations on the spatial ranges of the estimated effects, we generated densities by taking the average across multiple kernel density bandwidths, ranging from 1 kilometer to 500 kilometers. The result is a heat map representing the relative density of messages about a particular sentiment and concept, as illustrated in Figure 1, which shows the negativity toward the National Government

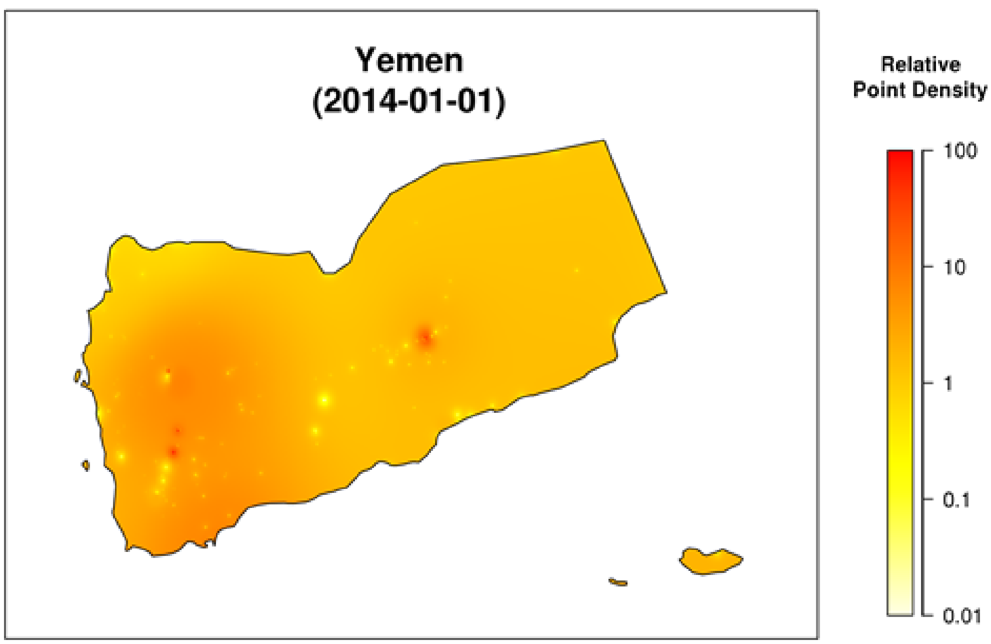

Figure 1. Heat Map. National Government Negative Tweets. January 2014.[74]

[72] Stan Openshaw and S. Openshaw, *The Modifiable Areal Unit Problem* (Geo Abstracts University of East Anglia, 1984).

[73] T. Camber Warren, "Mapping the Rhetoric of Violence: Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media," prepared for presentation at the Annual Meeting of the American Political Science Association, September 3–6, 2015, San Francisco, CA.

[74] Adapted from Twitter, unpublished data.

4. Dependent Variables

To attempt to validate the inferences derived from our new social media metrics, we rely on existing opinion poll data, collected by Gallup between November 14, 2013, and January 17, 2014, under the Global Research and Assessment Program (GRAP) for United States Special Operations Command (USSOCOM) J39. The poll consisted of 9,450 civilian Yemeni adults aged 16–65 with a sampling based on a stratified, multistage cluster design. The key advantage of this data source is that it provides anonymous measurements of political support for the Yemeni state and various insurgent groups, which can be geo-referenced to specific cities and towns, allowing researchers to generate an aggregate spatial representation of the sentiments recorded by the poll.[75]

All dependent variables were coded dichotomously.

Extremism Support and Extremism Opposition are derived from the Extremism index, which ranges from one to four and is a compilation of 25 questions concerning violent extremist organizations (VEOs), attitudes toward sharia, and jihad, with a Cronbach's alpha score of 0.62.

Institutional Support and Institutional Opposition are derived from the Institutional Confidence index, which is a compilation of 10 questions with a Cronbach's alpha score of 0.91. This index included questions about confidence in national government, state/provincial government, local/city government, military, police/law enforcement, financial institutions/banks, the national courts, sharia courts, tribal justice, and the electoral system.

Al-Qaeda Support and Al-Qaeda Opposition counted any responses indicating that either al-Qaeda's or AQAP's influence had a very positive influence as support. Similarly, any responses indicating these organizations had a very negative influence were counted as an opposition.

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75 Jones, *Counterinsurgency in Afghanistan.*

National Government Support and National Government Opposition are derived by counting responses indicating confidence in the national government, with indications of no confidence used as indicator of opposition to the national government.

5. Independent Variables

The independent variables are based on the heat maps generated from the sentiment and concept dictionary results. They change depending upon the evaluated dependent variable. Additionally, each independent variable forms the basis of a model set. These sets are evaluated in three different ways with demographic control variables, social media variables, or a combination of the two. We annotate these as DEMOGRAPHIC VARIANCE, TWITTER VARIANCE, and COMBINATION VARIANCE.

The independent variable extremism is the result of all words associated with VEOs and jihadist ideology as noted in the Sentiment Dictionary section. The independent variables are divided between either ***EXTREMISM POSITIVE***, which are based on the positive sentiment dictionary, or ***EXTREMISM NEGATIVE***, which is based on the negative sentiment dictionary. It is further broken down ***MONTHLY*** from October to January, and a ***TOTAL*** of all four months for a total of 10 extremism independent variables. Along the same lines each single organization was evaluated. For instance, in evaluating support for al-Qaeda, there is an ***AQ POSITIVE*** and an ***AQ NEGATIVE*** independent variable for each month, and a ***TOTAL*** of all four months for a total of 10 AQ independent variables.

The independent variable of ***INSTITUTION*** is the result of all words associated with institutions noted in the Sentiment Dictionary section. The institution variables are divided like the extremism variables. The institution variables are divided into the variables ***INSTITUTION POSITIVE*** and ***INSTITUTION NEGATIVE***. Insitution is further broken down into individual months, called ***MONTHLY*** from October to January with a ***TOTAL*** of all months for a combined 10 institution independent variables. Along the same line, the national government was evaluated. There is a ***NATIONAL GOVERNMENT POSITIVE*** and a ***NATIONAL GOVERNMENT NEGATIVE*** independent variable for most months, and a ***TOTAL*** of all the months for a total of 9 national government independent variables. There are fewer national government independent variables because there were not enough Twitter results to generate a positive heat map for the month of October for this search category.

6. Control Variables

Most of the control variables are based on demographic information. We did this to address a common critique against using social media data, which is that social media users are not a representative sampling of the population. Some may be concerned that if we find a significant relationship that appears to be driven by social media data, it may actually reflect demographic factors. Therefore, we controlled for a series of demographic factors that are known to influence political attitudes: Internet access, urban, gender, age, education, and wealth. All control variables were coded dichotomously.

The other control variables are derived from the Twitter density estimates. We controlled for both the overall number of tweets and the total number of tweets about a concept in a specific timeframe. We did this to account for the influence of total message volume so it could be differentiated from message content (e.g., sentiment). We also controlled for

Internet assigns a value of 1 to any use of the Internet, **Urban** is coded as 1 for urban areas with a population of at least 5,000 inhabitants. **Youth** counts those 24 years of age or younger, **Educated** counts those with at least some university education. This variable was dichotomously coded with those with at least some university education as 1 and everyone else as 0.

Wealthy - This control variable was derived from the Gallup Poll. It reflects Yemenis with an income of 60,000 Yemeni Riyals (YER) per year or higher. Anyone earning at least 60,000 YER was dichotomously coded as 1 and those below that amount as 0.

We also control for background spatial characteristics:

Population Density - This control variable is derived from a population density heat map and reflects a more refined impact of population in the urban areas.

Total Tweets - This control variable is derived from the combination of heat maps for each month from October 2013 through January 2014. It is the sum of all tweets originating from Yemen during this timeframe. This variable was log transformed in order to account for its heavy tailed distribution.

Total Concept Tweets - This control variable is based on the combination of heat maps that relate to each of the independent variables. It encompasses the months of October 2013 to January 2014. It is the sum of all tweets that relate to a specific topic (e.g., extremism, national government) during the specified time. This variable was also log transformed in order to account for its heavy tailed distribution.

Provincial Boundaries - This control variable is based on the 20 provincial political boundaries and the capital city boundary within Yemen. These were included as fixed effects in the models.

C. REGRESSION ANALYSIS

We used a logistic regression for our analysis. Logistic regressions are a statistical method in which the dependent variable is dichotomous, also known as logit regressions, or the logit model. Dichotomous dependent variables can take only two values, such as one/zero, win/lose, or alive/dead. The logistic model is used to estimate the probability of a binary response based on one or more independent variables.[76]

In summary, we assessed eight dependent variables that were derived from existing opinion polls. The dependent variables focus on support for or opposition to the government and support for or opposition to the insurgency. After developing the dependent variables we built 39 independent variables that derived from positive and negative Twitter sentiment. Finally, we controlled for a variety of factors related to the dependent and independent variables. In the end, we experimented and evaluated 117 different models.

[76] Cox, "The Regression Analysis of Binary Sequences."

V. RESULTS

Taken as whole, these statistical models generate five major categories of results. First, we find that the addition of social media metrics consistently improves the level of predictive success when assessing popular sentiments, over and above the predictions generated by demographic patterns alone. Second, we find that using our method, we are able to generate estimates of spatial patterns of sentiment that strongly resemble estimates derived from traditional polling methods. Third, it seems that this congruence is strongest when our method was used to identify oppositional sentiments, as opposed to supportive sentiments. Fourth, our methods yield better and more consistent results when examining VEO's and extremism, than when examining support for the government. Finally, when we examine data by month, even controlling for background spatial patterns and demographic patterns, we find that the social media data still provides an important improvement in the predictive success of the models.

A. FINDING ONE – IMPROVES PREDICTIONS

The most significant and reliable finding is that Twitter-derived sentiment metrics strengthens the predictive success of the statistical models. Every model with Twitter and demographic data combined resulted in better AIC scores than those models with either demographic or Twitter data by themselves. Why is this important? The AIC score is basically a comparison tool that helps us evaluate the predictive success of each model.[77] The AIC measures how well a specific model fits a dataset, which in this case are estimates of political support and opposition. It also considers the number of variables, penalizing those models that are so flexible that can just as easily fit any dataset. Most importantly the AIC score is an indicator of confidence in a model.

When examining the findings presented in Table 1, it is important to note that the lower the AIC score is, the more confidence we should have in the model. These eight model sets are those with the ***TOTAL*** independent variables. We believe that these

[77] Hirotugu Akaike, "A new look at the statistical model identification." *IEEE transactions on automatic control* 19, no. 6 (1974).

particular models are the most reliable, because they encompass Twitter data for the same time period that the original opinion poll was conducted. The results on the far right show the AIC scores for each of the combined models, supporting our claim of improved predictive success across the board.

Table 1. Akaike Information Criterion.

DEPENDENT VARIABLES	Demographics	Twitter	Combined
Al Qaeda Support	612.572	649.248	541.813
Al Qaeda Opposition	9,423.769	9,700.528	8,134.125
Extremism Support	5,144.949	5,387.780	4,299.991
Extremism Opposition	3,103.926	3,483.122	2,857.858
National Govt Support	6,592.986	6,443.039	5,764.233
National Govt Opposition	9,479.310	11,007.990	8,754.131
Institution Support	8,459.854	8,322.456	7,297.280
Institution Opposition	9,914.237	10,735.100	8,576.029

B. FINDING TWO – SIMILARITY OF SPATIAL PATTERNS

Closely related to the first finding is that the estimates derived from social media generate similar patterns of inferences to those generated by traditional polling data. There are two ways to demonstrate this finding. The first is a statistical approach and the other is a visual depiction. Statistically, 30 out of the 39 TWITTER VARIANCE models show a better AIC than the DEMOGRAPHIC VARIANCE models. The only model sets that do not show that the TWITTER VARIANCE is better are those with ***National Government Support*** and ***Institutional Support*** dependent variables.

The other way to demonstrate this is through the visual depiction in Figure 2, which shows a comparison of polling and twitter sentiment by province. The heat map on the left is the mean of all polling responses concerning AQ and AQAP by province. The darker the color means there is a greater the level of opposition. The heat map on the right is the mean of all negative tweets about AQ and AQAP from October to January by province. The darker color is there is a greater amount of negative tweets. As you can see from the maps, the majority of the provinces are closely aligned with the exception of eastern Yemen, an extremely rural region with little to no Internet access.

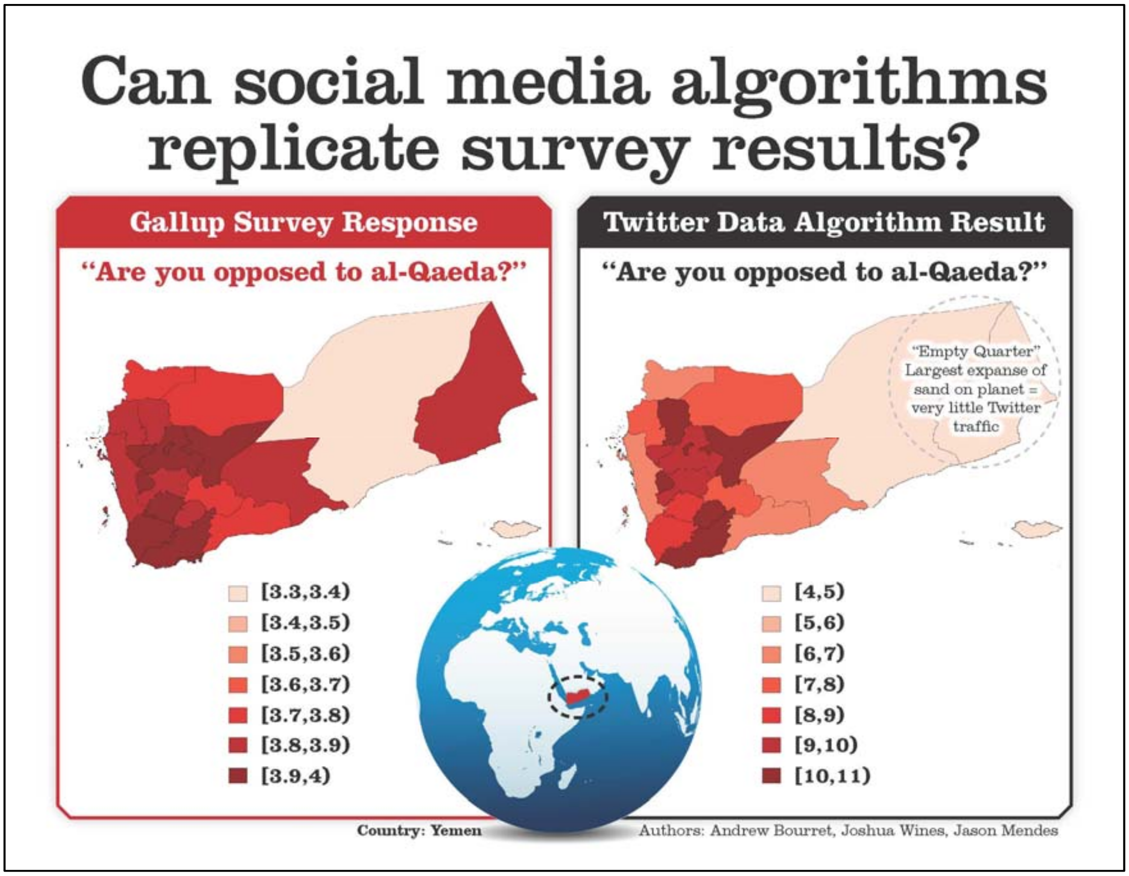

Figure 2. Comparing Survey Responses and Twitter Metrics Indicating Opposition to al-Qaeda.[78]

This is not to assert that our research finds that twitter sentiment can be used in lieu of polling. There are too many inconsistencies between the different models to definitively make such a claim. The purpose is to highlight the competitiveness between the impact of twitter data and demographic data on polling sentiment. It is simply another step in confirming or denying the value of social media as a source of data-driven insights.

[78] Adapted from Gallup survey, unpublished data; Twitter, unpublished data.

C. FINDING THREE – SENTIMENT MATTERS

Interestingly, our results also indicate that Twitter is more suitable for picking up certain types of information. For example, the results in Table 2 indicate that negative sentiment may be more reliable. These results are the only ***TOTAL*** independent variables assessed using the **Combination Variance** that had statistically significant coefficients. Just as importantly, they show a positive relationship between polling and twitter sentiment. As mentioned earlier in Finding One, we have the greatest confidence in the ***TOTAL*** independent variables and the **Combination Variance** always has the best AIC. These relationships can be found looking at 1) the ***AQ Negative Sentiment*** row under the ***al-Qaeda Opposition*** combined column; 2) the ***Extremism Negative*** sentiment row under the ***Extremism Opposition*** combined column.

Table 2. Combined Negative Sentiment.

	Al Qaeda Opposition			Extremism Opposition		
	Demographics	**Twitter**	**Combined**	**Demographics**	**Twitter**	**Combined**
Internet Users	0.317*** (0.122)		0.254* (0.141)	-0.127 (0.201)		-0.158 (0.246)
Urban Residents	0.038 (0.073)		0.148* (0.086)	-0.062 (0.146)		-0.033 (0.167)
Men	1.226*** (0.054)		1.271*** (0.058)	-0.564*** (0.102)		-0.750*** (0.117)
Youth	0.087 (0.056)		0.052 (0.061)	0.259** (0.104)		0.176 (0.116)
Educated	0.537*** (0.111)		0.605*** (0.125)	0.047 (0.162)		0.242 (0.183)
Wealthy	0.391*** (0.066)		0.386*** (0.073)	0.138 (0.121)		0.083 (0.134)
Population Density	0.016 (0.034)		-0.022 (0.039)	-0.080 (0.063)		-0.120 (0.077)
AQ Negative Sentiment		2.012*** (0.235)	0.799*** (0.305)			
Total AQ Tweets		-1.281*** (0.328)	-1.089** (0.428)			
Extremism Negative Sentiment					2.405*** (0.332)	0.822* (0.486)
Total Extremism Tweets					-2.409*** (0.632)	0.208 (0.753)
Total Tweets		-0.132*** (0.036)	-0.027 (0.062)		-0.406*** (0.084)	-0.093 (0.148)
Constant	-0.191 (0.227)	-1.764*** (0.408)	0.163 (0.599)	-2.535*** (0.446)	-5.260*** (1.030)	-4.759*** (1.541)
Province fixed effects	NA	Included	Included	NA	Included	Included
AIC	9700.528	9423.769	8134.125	3483.122	3103.926	2857.858

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Columns are comprised of two values. Numbers on the left side of each column are coefficient values. Numbers to the right side of each column are standard error.

Even in the negative ***Total*** independent variables with ***Twitter Variance***, only one model with a statistically significant coefficient showed a negative relationship (Table 3).

This reinforces the finding that sentiment is potentially better at evaluating negative sentiment.

Table 3. Significance in Expected Direction (Total).

DEPENDENT VARIABLES	Expected	Unexpected	Insignificant
Al Qaeda Support	X		
Al Qaeda Opposition	X		
Extremism Support	X		
Extremism Opposition	X		
National Govt Support		X	
National Govt Opposition			X
Institution Support		X	
Institution Opposition		X	

When we looked at the reliability of positive sentiment, we found some additional supporting arguments. For example, there was only one other ***TOTAL*** independent variable model we assessed using the COMBINATION VARIANCE that had statistically significant results. This was the ***National Government Support*** model, but it had a negative relationship between twitter and polling (reference Table 4). This result along with the negative relationship found in the ***Institutional Support*** TWITTER VARIANCE model seems to reinforce the finding that negative sentiment is more reliable. We infer that Twitter data is a reliable source of ground truth when there is a positive relationship between positive twitter sentiment / polling support and negative twitter sentiment / polling opposition. Based on this analysis, it seems like those that spoke negatively on twitter were likely to be in the same geographic space as those that spoke negatively in the survey.

Table 4. Combined Sentiment.

	National Government Support			Institutional Support		
	Demographics	**Twitter**	**Combined**	**Demographics**	**Twitter**	**Combined**
Internet Users	-0.338** (0.158)		-0.419** (0.175)	-0.205 (0.125)		-0.283** (0.143)
Urban Residents	-0.292*** (0.101)		-0.275** (0.114)	-0.169** (0.082)		-0.161* (0.092)
Men	-0.277*** (0.067)		-0.337*** (0.071)	-0.602*** (0.057)		-0.612*** (0.061)
Youth	0.059 (0.074)		0.098 (0.077)	0.121* (0.062)		0.186*** (0.065)
Educated	-0.166 (0.129)		-0.145 (0.137)	-0.237** (0.109)		-0.208* (0.118)
Wealthy	0.188** (0.080)		0.199** (0.086)	0.039 (0.070)		-0.002 (0.075)
Population Density	0.019 (0.045)		0.086 (0.054)	-0.057 (0.038)		-0.023 (0.044)
Natl Govt Positive Sentiment		-0.665*** (0.102)	-0.491*** (0.145)			
Total Natl Govt Tweets		0.342*** (0.130)	0.247 (0.253)			
Institution Positive Sentiment					-1.324*** (0.351)	-0.056 (0.443)
Total Institution Tweets					0.694** (0.338)	-0.096 (0.475)
Total Tweets		0.077* (0.046)	-0.249*** (0.087)		0.451*** (0.035)	-0.174*** (0.060)
Constant	-2.271*** (0.315)	-0.729* (0.392)	-3.346*** (0.797)	-0.752*** (0.254)	2.546*** (0.290)	-1.333** (0.570)
Province fixed effects	NA	Included	Included	NA	Included	Included
AIC	6443.039	6592.986	5764.233	8322.456	8459.854	7297.280

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

Columns are comprised of two values. Numbers on the left side of each column are coefficient values. Numbers to the right side of each column are standard error.

If true, this may mean that the negative sentiment dictionary is perhaps better due to translation. However, previous research shows that sentiment dictionaries that are machine translated perform only slightly worse than manually created dictionaries.[79] The other possible explanation is that Yemeni Twitter users that express negative sentiment are a more representative sample of the population. This would be consistent with other research that states social media in the Middle East functions as a "free space" for criticism.

D. FINDING FOUR – THE IMPORTANCE OF THE TOPIC

The story does not end there. Some of the other results challenge the third finding. For example, every extremism and AQ related model with ***MONTHLY*** independent variables (e.g. October, November, etc.) using the COMBINATION VARIANCE or TWITTER VARIANCE results in statistically significant coefficients and a positive relationship. This is regardless of whether the independent variable is based on either

[79] Saif M. Mohammad, Mohammad Salameh, and Svetlana Kiritchenko, "How Translation Alters Sentiment," *Journal of Artificial Intelligence Research* 1 (2015): 95–130.

positive or negative sentiment. In contrast, only the ***National Government Support*** and the ***Institutional Support*** models have relationships in both the expected and unexpected direction. This contrast is seen in Table 5, which distills the results of all of the ***MONTHLY*** independent variables using either the COMBINATION VARIANCE or TWITTER VARIANCE. It captures any ***MONTHLY*** statistically significant coefficient that has a positive or negative relationship between twitter and polling. As you can tell, it seems that certain concepts are easier or more feasible to evaluate.

Table 5. Significance in Expected Direction (Any).

DEPENDENT VARIABLES	Expected	Unexpected
Al Qaeda Support	x	
Al Qaeda Opposition	x	
Extremism Support	x	
Extremism Opposition	x	
National Govt Support		x
National Govt Opposition	x	x
Institution Support	x	x
Institution Opposition	x	x

These inconsistencies point to the possibility that the dictionary didn't adequately capture the concepts of national government and/or the institution index. However, there were 51 separate terms associated with national government and 890 separate terms associated with the institution index. It's unlikely the inconsistencies are due to a deficient dictionary. It's also possible that individuals that tweet negatively about the government are less likely to self-identify their location in their profile out of fear. However, there are negative relationships even among those that tweet positively about the government and positive relationships among those that tweet positively about AQ. Fear of the government does not seem to fit as an answer. It may simply be that it's more difficult to evaluate concepts regarding the government compared to AQ and extremism.

E. FINDING FIVE – POTENTIAL TO EVALUATE BY MONTH

Lastly, we evaluated each dependent variable using the ***MONTHLY*** positive and negative independent variables. This was the case for each model except for ***NATIONAL GOVERNMENT POSITIVE*** sentiment. As noted earlier, there weren't enough Twitter data points to make a heat map for the month of October. The value of running so many models with different independent variables allowed us to examine the reliability of monthly data. In fact, we looked at 35 model sets of ***MONTHLY*** independent variables.

These models indicate that monthly Twitter sentiment may also be reliable. We stated in Finding One that we have the greatest confidence in the ***TOTAL*** independent variables. However, even the majority of the ***MONTHLY*** independent variable produces results with statistically significant coefficients in the expected direction. Table 6 captures the number of the ***MONTHLY*** TWITTER VARIANCE models with statistically significant coefficients. Out of those 27 models, 18 of them show a positive relationship. These statistical outputs are important, because they influence our confidence level in the reliability of the data. While these results aren't as statistically strong as the previous findings, they do indicate there is a significant relationship between monthly Twitter data and polling results.

Table 6. Significance in Expected Direction (Monthly).

DEPENDENT VARIABLES	October	November	December	January
Al Qaeda Support	Expected		Expected	
Al Qaeda Opposition	Expected	Expected	Expected	
Extremism Support	Expected	Expected	Expected	Expected
Extremism Opposition	Expected		Expected	Expected
National Govt Support	Unexpected	Unexpected	Unexpected	Unexpected
National Govt Opposition	Unexpected	Expected	Unexpected	Expected
Institution Support	Expected	Expected	Unexpected	
Institution Opposition	Expected	Unexpected	Unexpected	Expected

VI. CONCLUSION

Our thesis asked whether social media analysis could be a reliable proxy for polling in a conflict zone. We decided to pursue this research question after identifying several gaps. First, we examined the importance of traditional collection and assessment methods in determining a population's attitudes, beliefs, and opinions, specifically in low-intensity conflicts. During our research, we identified a deficiency in the U.S. military's doctrinal assessment methods. Primarily, we noted a need to evaluate popular support more often than traditional methods afford, especially in areas outside major combat operations.

This subsequently led us to examine different ways social media data is being used, and we identified sentiment analysis as the most appropriate way to evaluate this data. However, there was one specific aspect missing from the existing literature: the assessment of the relationship between geo-spatially anchored social media users and traditional polling methods. In response, we designed an approach centered around examining geo-spatially anchored data, allowing us to assess whether people in the same general location express the same sentiment in both measurement approaches.

During the analysis phase of our research, we examined dependent variables derived from existing polling data, alongside newly developed independent variables derived from Twitter messages. What we found in response to our question and research method was something unexpected—sentiment analysis of Twitter data has an additive positive value when compared to polling data, and metrics derived from Twitter messages may offer a reliable source of data under certain conditions.

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VII. ADDITIONAL RESEARCH

Our team identified two broad areas of potential future research. They are sentiment research and operational changes. The following recommended research areas are not limited in value to the U.S. government.

A. IMPACT OF SENTIMENT

Additional research is required to find out whether sentiment or topic selection under different conditions produces more reliable results as noted in this research. We believe it would be beneficial to determine whether sentiment dictionaries other than the ones we chose would provide different research outcomes. In particular, we recommend additional research to determine the impact of sentiment dictionary lists. We recommend using the same data and approach to establish a baseline in order to compare as many lists as are available. We also recommend developing AFINN dictionaries, at least for all high-interest areas. An Arabic AFINN would have been immeasurably helpful for this research and would have eliminated the need for translation. We recognize the potential negative impact of translation, so further research is also required to improve automated translation. This is especially true for the languages spoken in conflict areas and/or high-interest areas.

B. EVALUATION OF THE TOPIC

Our research indicates that the reliability and relationship of sentiment results vary by topic. However, only four topics were evaluated. What is needed is a deeper examination of which topics generate more reliable results using this data and data for other countries. This will help analysts identify gaps in social media data reliability.

C. DOES THE COUNTRY/REGION MATTER?

We believe it is important to determine whether our research method can be duplicated in other countries or regions. In particular, are there different outcomes for countries that are at peace versus those in conflict?

D. GEO-LOCATION

One explanation for the statistically insignificant results and inverse relationships found in our research is that there simply were not enough tweets in Yemen. Increasing the number of available geo-located data points would improve the reliability of our research. Additionally, more data could help shed light on the role online obfuscation plays. When online users obscure their location or identity, does this change the content of their tweets? Are they more or less honest? Does this impact the sentiment and focus of criticism or praise for the government or insurgent groups? Along the same lines, the USG should require latitude and longitude for all future contracted and executed polls in order to conduct robust geo-spatial analyses.

E. INTEGRATION OF SOCIAL MEDIA ANALYSIS

As noted at the beginning of the chapter on results, social media data combined with polling data produces a better and more reliable model of analysis. Analysts should conduct social media analysis and combine the results with polling analysis to support operational assessments.

APPENDIX. CONCEPT DICTIONARY

Extremism & AQAP	Extremism & AQ	Extremism & AS	Extremism & AA
AQAP	AQ	Ansar al Shariah	Ansar Allah
AQ in Yemen	al-Qaeda	AAS	Houthi militants
al-Qaeda in Yemen	al zawahiri	ASY	Houthi fighters
al-Qaeda in the Arabian Peninsula		Hamza al Zinjibari	Houthi rebels
Qasim al-Raymi		Jalal Baleedi	Houthi militia
Sheikh al-Raymi		Hamza al-Zinjibari	Yahia Badreddin al-Houthi
Emir al-Raymi			Abdul Malik Badreddin
Nasir al-Wuhayshi			Abu Ali Abdullah al Hakem
Sheikh al-Wuhayshi			
Emir al-Wuhayshi			
Extremism & Jihad	**Extremism & Sharia**		
Aden-Abyan	Sharia		
Islamic Army	Islamic Court		
Abdul-Karim			
Jihad			
Wahhabi			
Salafi			

Institution & Military	Institution & Military cont'd	Institution & Police	Institution & National govt
Yemeni Military	Yemeni Air Force	Law enforcement	ROYG
Our Military	Yemeni Airmen	Central Security	Government
Our Military Leadership	Yemeni Airman	Police	President
Yemeni military leaders	Our Air Force	Security Forces	Prime Minister
Military Council	Our Airmen	Government forces	Parliament
Military Leaders	Yemeni Fighter Jets	Political Security Organization	Yemeni Council
Yemeni Security Forces	Our Fighter Jets	National Security Bureau	Yemeni Regime
Yemeni Armed	Yemeni Navy	Counter-Terrorism	Republic of

Forces		Unit	Yemen
Our Security Forces	Our Navy	Ministry of Interior	Political Leaders
Our Armed Forces	Our Sailors	Minister of Interior	
Our Troops	Yemeni Battleship	Criminal Investigation	
Yemeni Troops	Our Forces	Abdel-Qader Qahtan	
Yemeni Army	Our Government Forces	Abdel Qader Qahtan	
Our Army	Yemeni Forces	CSF	
Our Soldiers	Yemeni Government Forces	NSB	
Yemeni Soldiers	Yemeni Republican Guard	CTU	
Our Republican Guard	The Ministry of Defense in Aden		
Yemeni Ministry of Defense	Our Ministry of Defense		
Yemeni Minister of Defense	Mohammed Nasser Ahmed		
Institution & Local govt	**Institution & National govt**	**Institution & Federal Court**	**Institution & Tribal Justice**
Local government	ROYG	Justice System	Tribal justice
City government	Government	Court	Tribal court
Mayor	President	Judges	
City Manager	Prime Minister		
City Council	Parliament		
My Municipality	Yemeni Council		
Municipal council	Yemeni Regime		
Institution & Bank	**Institution & Elections**	**Institution & State govt**	
Yemeni bank	Electoral	Governor	
SBYB	Election		

Notes: The Extremism annotation in the first table indicates that all these terms are associated with the concept of extremism in addition to the 6 subcategories of extremism. The Institution annotation in the second table indicates that all these terms are associated with the concept of institution in addition to the 10 subcategories of Yemeni institutions. This is not an exhaustive list with spelling and punctuation variations removed along with the Arabic translation.

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