Do Politics Stop at the Water's Edge? Evidence from Twitter Discussions on Afghanistan Withdrawal

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Abstract How does political division in the United States influence Twitter discussions about foreign policy? Recent research has produced mixed results, ranging from the partisanship approach that sees foreign-policy polarization as an extension of domestic polarization to bipartisanship-based explanations in which Americans rally around the flag when it comes to foreign affairs. Using ideology estimation, sentiment analysis algorithms, and unsupervised topic modeling on tweets about the U.S. withdrawal from Afghanistan, this paper provides support for a more nuanced view that polarization fluctuates depending on the foreign event. We propose that even within that event, cross-cutting ideologies may converge based on the sub-topics. More specifically, while both liberals and conservatives joined the discussion on the withdrawal, the former focused more on the humanitarian aspects of the event, such as women's situation in Afghanistan and calls for help for the country. On the other hand, conservatives concentrated more on the issues regarding who was to blame for the consequent humanitarian failure. We also analyzed the links between sentiments, ideology, and bot accounts and found that both negative sentiments and bot accounts were significantly associated with conservative users.

In April 2021, when president Joe Biden announced the withdrawal of all remaining troops from Afghanistan by September, nobody expected such a rapid takeover. The U.S. intelligence community estimated that it would take at least six months before the Afghan army gave up; yet, it only took weeks for the Taliban to regain the capital city and majority of the country. The U.S. soldiers left the country in a hurry, leaving many Afghan allies behind.

The withdrawal was a historical event for the U.S. as it marked an end to a two-decade war with not much of a success story. In Washington, both Democrats and Republicans gave strong remarks on the event. Referring to president Biden, for example, Senator Richard J. Durbin firmly sided with the decision: "He made the difficult decision to not hand over this longest of American wars to a fifth president, and had he walked away from the withdrawal agreement originally negotiated by President Trump, Taliban attacks on U.S. forces would have restarted and required

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yet another surge in U.S. troops."[1]. The Republican politicians, however, were not entirely happy with the resulting chaos in Afghanistan. Senator Mitch McConnell said that the foreign powers were "watching the embarrassment of a superpower laid low."[2]. The echoes of discussion on the withdrawal were not limited to Washington's political arena. As social media flooded with the footage of Afghan people hanging on the U.S. planes, ordinary people posted about 16.5 million tweets by our estimations[3]. Just like the political elites, the public was also divided in their reactions: According to a Pew poll conducted in August 2021, about 54% of American adults supported the withdrawal decision, while 42% found it wrong[4]. This division was mostly on ideological lines: While most Republicans said the withdrawal was a wrong move, the majority of Democrats thought it was the right action. Both groups agreed on one thing, however, that the U.S. failed in achieving its goals in Afghanistan.

The question of why people had divergent opinions on Afghanistan withdrawal is part of a broader question: Does politics stop at the water's edge, or do we see the reflections of domestic polarization on foreign policy decisions as well? The literature on foreign policy polarization provides us with mixed empirical results. The research on social media polarization has a similar debate: Do social media users live in 'echo chambers' where they are only exposed to similar political views, or do we observe cross-cutting ideologies that decrease polarization? In this paper, we bring evidence for a more nuanced view in both scholarships, i.e. the political polarization on foreign affairs or social media is issue-specific. Polarization levels fluctuate not only by foreign events (Afghanistan withdrawal) but even within the same event; they can fluctuate by sub-topics (women's rights in Afghanistan). Our evidence also supports the cross-cutting ideology argument for Twitter: Users may cluster around ideology, but when a major event breaks out, liberals and conservatives can converge in some subtopics, such as military failure, while differentiating in other issues like Biden's mismanagement of the process.

We first gathered tweets discussing the United States' withdrawal from Afghanistan to see how polarization varies within a discussion. Then, we estimated users' ideologies and removed bot/spam accounts to give our dataset the final shape. Using these newly estimated variables as covariates, we applied unsupervised structural topic modeling and sentiment analysis on Twitter data for 32,831 unique Twitter users. This allowed us to investigate how ideology influenced the themes discussed and how sentiments relate to topics and ideologies. We found that people were likely to post about the same topics with only a few exceptions.

Liberal users, in particular, focused on the humanitarian aspect of the case, such as

1. Edmondson 2021.

2. Edmondson 2021.

3. These estimates were obtained using the count tweet parameters via Twitter REST API v2, and we counted English tweets sent globally on Afghanistan withdrawal between May 1 and mid-November 2021. For a detailed graph on the change of tweet counts by time, see Appendix Figure 7.

4. Green and Doherty 2021.

Afghan women's predicament under the new Taliban control or appeals for assistance for Afghanistan. Conservative users, on the other hand, were more likely to focus on topics related to the current administration, like Biden's handling of the crisis and abandonment of American allies. Our findings also suggest that conservatives were positively associated with bot accounts despite posting more tweets. Finally, we discover that sentiment is inversely correlated with ideal point scores, implying that conservatism is associated with a higher likelihood of tweet negativity.

Related Literature

The consensus among polarization researchers is that the general political polarization in the U.S. has steadily increased since the 1970s, both in the political elites and among the mass public, without showing any significant signs of reversing the trend.[5]. This steady increase "has forced acknowledgment that we have shifted from a system marked by low polarization to one of high polarization"[6].

Foreign policy polarization, however, can be distinguished from domestic polarization due to the different dynamics at play. First, most foreign policy decisions are not at the top of the public's priority list[7]. Second, in foreign-policy polarization, there is a greater informational asymmetry between the public and legislators, and even between legislators and the president, than there is in domestic politics[8]. As a result, the debates in this scholarship differ from the domestic polarization literature in that there are two main contending arguments. The first, which we term 'politics stops at the water's edge' after Arthur Vanderberg's famous phrase, can be explained by the 'rally around the flag' effect, in which external threats cause the public to rally behind the president to safeguard national interests[9]. The second approach claims that polarization on foreign policy matters is less intense than on domestic policy[10]. Chaudoin, Milner, and Tingley (2010) supports this assertion with poll data and congressional bills, demonstrating that substantive votes do not indicate an increase in polarization since the 1970s: "Presidents can still construct bipartisan coalitions in support of their preferred foreign policies if they so desire"[11]

The second line of reasoning claims that, like domestic politics, ideological polarization has now won out in foreign policy issues and that party votes from Republicans and Democrats have diverged dramatically since the early 1970s. "Americans are at least as polarized on issues of foreign affairs as they are on domestic politics."

5. Hetherington 2009; Jacobson 2010; Layman, Carsey, and Horowitz 2006; Levendusky 2009; Poole and Rosenthal 1984; Stonecash, Brewer, and Mariani 2019; Theriault 2008.
6. Pierson and Schickler 2020, p.38.
7. Doherty et al. 2022.
8. Baum and Groeling 2010.
9. Mueller 1971.
10. Busby and Monten 2012.
11. Chaudoin, Milner, and Tingley 2010, p.78.

writes[12]. Colaresi (2007), for example, claims that there is an information asymmetry on foreign events between the ordinary people and politicians because the latter have access to privileged information on security and military matters. According to this argument, people are more likely to adopt 'elite-cues' from their respective ideologies as a result of this asymmetry, according to the argument, resulting in a more politically polarized conversation atmosphere. "Bipartisanship in foreign policy is now 'dead'." says Kupchan and Trubowitz (2007), summarizing this line of reasoning.

Apart from these two opposing viewpoints, a third approach offers a more nuanced explanation, namely, that polarization on foreign policy is based on various circumstances. While Hurst and Wroe (2016) shows that polarization levels on foreign policy show cynical patterns of increasing and decreasing over time, Jeong and Quirk (2019) concludes that polarization on foreign policy is influenced by three factors: (i) partisan electoral rivalry, (ii) general domestic ideological polarization, and (iii) foreign-policy events. For the partisan electoral rivalry, congress members would simply assume that the election of a co-partisan president would boost their chances of re-election[13]. For the second one, foreign policy polarization is a continuation and reflection of domestic ideological polarization on the liberal-conservative spectrum[14]. As for the last one, the rationale is that polarization levels are issue-specific. When the Cold War ended, for example, the American public had no 'common enemy' anymore. As a result, increased levels of foreign-policy polarization are expected in the post-Cold War era. In the case of Afghanistan, public support from both conservatives and liberals was strong at the beginning of the war. Nevertheless, as the conflict prolonged, the divide in support between the two ideologies grew[15].

Thus far, we have discussed literature about elite behavior and public opinion surveys. On the other hand, as a political medium, Twitter may have different dynamics of conversation than the general population because its users are more likely to be younger, live in cities, are highly educated, male, and white[16]. We can also derive two opposing arguments from the literature on Twitter polarization: Cross-cutting ideologies v. echo chambers. Users' proclivity to follow and communicate with others in their ideological circles is referred to as echo chambers[17]. In such circles, people are more politically polarized than in real life because of the hyper-fragmented nature of Twitter[18]. On the other hand, the cross-cutting ideologies approach asserts that people are more exposed to views from other ideological positions, reducing political polarization[19]. The more nuanced perspective here is about the context's importance: "The role of the political context in shaping user clusterization should

12. Yankelovich 2005, p.2.
13. Kriner 2010.
14. Hurst and Wroe 2016.
15. Jacobson 2010.
16. Hargittai 2020; Barberá and Rivero 2015.
17. Colleoni, Rozza, and Arvidsson 2014.
18. Baum and Potter 2019.
19. Barberá 2015b.

not be underestimated."[20].

Our position will be consistent with the more nuanced approaches expressed in both scholarships: It is difficult to make generalizations about the existence of a clear trend on foreign-policy polarization or Twitter polarization. Instead, people's ideological divisions are more case-specific. While there may have been intense polarization during the Vietnam War[21], polarization on the Afghanistan issue may not have been as high. Furthermore, we argue that, within a given international event, users from both ideological positions may be able to coexist in the same conversation (like the U.S. military failure in Afghanistan) and diverge from each other only on some matters (as in whose fault was the devastating result of the withdrawal). This reasoning also supports the third approach to Twitter polarization: While users generally tend to cluster along ideological lines[22], some subtopics can bring them together.

Data and Methodology

Our primary data for text analysis consist of tweets posted between May 1, 2021, and January 7, 2022. To define our search parameters, we first inspected a random sample of 100 tweets and the major news about the withdrawal after May 2021. Then, based on the most commonly used words in these sources, we produced an initial list of keywords, including Afghanistan, Taliban, Ashraf Ghani, Kabul, and Pashtun. To finalize the keyword list, we searched for semantically similar words in our initial list through GloVe. GloVe is an open-source, unsupervised vector presentation algorithm which is based on word co-occurrence statistics[23]. Its pre-trained mechanism allows researchers to explore the semantically closer words in the word vector space. Using Twitter REST API v2 through twarc2[24], then, we extracted all tweets that fulfilled three criteria: they had to have at least one of the keywords, they had to be from the United States, and they had to contain at least one of the keywords.[25]. The eventual dataset consisted of 123,341 tweets and 32,831 users. Because the method is based on whom individuals follow on Twitter, we also needed to create a new dataset for ideology estimation. To do so, we used the authors' information in the primary dataset to extract the user IDs that they follow.

Before implementing the topic modeling, we first wanted to remove bot/spam accounts from the dataset. This is a significant issue because the number of bot

20. Bodrunova et al. 2019, p.119.
21. Beinart 2008.
22. Barberá 2015b.
23. Pennington, Socher, and Manning 2014.
24. Summers et al. 2022.
25. We certainly know that these users were from the U.S. When we realized that it is near-impossible to do ideology estimation for hundreds of thousands of users given Twitter's rate limits, we switched to the idea of using a sub-sample instead of the universal set of tweets on the withdrawal. Hence, the best subsampling criteria were to filter tweets that we are sure were from the U.S. and were in English.

accounts has risen with the increase in social media usage. A bot user is a software program rather than a human being who interacts with other social media users and posts automatically[26]. These bot accounts, especially in political science research, can quickly introduce bias and disrupt data analysis[27]. As a result, bot accounts funded by political campaigners could easily lead us to reach conclusions that are simply not there. To address this issue, we investigated how bot accounts are linked to ideology, then excluded them from the dataset before applying topic modeling. We used a supervised machine learning classifier for bot removal, Botometer v4[28]. The algorithm examines over 1000 features for a given Twitter account, which could be classified into six broad categories: user profile, friends, network, content, language, and sentiment[29]. The final output of the Botometer is a score ranging from zero to one, with higher numbers indicating a higher likelihood of being a bot/spam account. We looped through individual accounts in the primary dataset to extract these probabilities for each user and calculated their bot scores. Then, we removed these bot accounts using the threshold of 0.43 on the 0-1 scale as suggested by the algorithm's developers.

We then generated an ideal point score for each account using a previously validated computational model created by Barberá et al. (2015), which exploits Twitter users' social networks to infer latent political preferences. This method is akin to estimating ideology based on a roll-call vote. Instead of using votes, Barberá et al. (2015) utilizes data from Twitter users' friends. The procedure is based on the homophily assumption: Because of the informational costs, people on Twitter are more inclined to follow others who hold similar ideological positions. Since users have only limited time to absorb new information, when they decide to follow someone, they also decide not to follow alternate information sources as an opportunity cost[30]. Following users with opposing ideologies might also cause cognitive dissonance if the information they supply is incompatible with one's own ideological background[31]. Because of these trade-offs, people follow political accounts with similar ideological stances.

The original ideology estimation method for Twitter users is based on the Bayesian spatial following model[32]. It is validated through real-world party affiliation data and ordinary people's campaign donation records, yielding an overall accuracy of over 90%. However, because the Bayesian spatial model iterations require extensive computational power, Barberá et al. (2015) proposed a multidimensional scaling technique based on correspondence analysis. We chose the latter since it achieves the same results as the former.

Random effects at the user and elite levels are also taken into account by the

26. Yang, Ferrara, and Menczer 2022; Luceri et al. 2019.
27. Wirth, Menchen-Trevino, and Moore 2019.
28. Sayyadiharikandeh et al. 2020.
29. Varol et al. 2017.
30. Barberá 2015a.
31. Iyengar and Hahn 2009.
32. Barberá 2015a.

ideology estimation approach. It adds a parameter for a user's political interest (number of elites they follow). If a person follows many political accounts, she might just be a political activist. On the elite level, it considers the popularity of the user: If a political elite (e.g., Barack Obama) has millions of followers, it is more likely that this is due to their popularity than to a user's ideological proximity. By running the model for approximately 64 million users in the United States, Barberá (2015a)'s package was last updated in August 2020.

To begin ideology estimation, we first extracted the list of accounts that each user in our dataset follows on Twitter. Matching the list of accounts each user follows with the pre-estimated ideology scores of elites (politicians, news outlets, think tanks, etc.), we then identified each user's ideology in a liberal-conservative axis. The resulting ideology scores are normalized with a normal distribution around a mean of zero and a standard deviation of one and range from -2.5 (very liberal) to 2.5 (very conservative). We removed users whose ideology could not be estimated because they were not following any elite political accounts. Figure 1 shows the resulting ideology distribution for tweets and users. While the number of individuals who tweeted on the pullout from Afghanistan is comparable between conservatives and liberals, the former posted far more. More specifically, conservatives dominated the conversation, accounting for 62% of total tweets and 55% of unique authors. We also examined the distribution of tweets and ideologies of users across the U.S. in Figure 2[33].

When people from different ideologies meet in the same subtopic, how similar are their reactions? Conservatives and liberals may discuss the same topic, yet their perspectives and feelings could vastly differ. To understand whether they are indeed different, we measured sentiments of tweets using Valence Aware Dictionary and sEntiment Reasoner (VADER)[34]. VADER is a sentiment analysis tool that uses a lexicon and a set of rules to perform well on brief and informal documents like tweets. According to recent scholarship, VADER produces fairly accurate sentiment results on Twitter data on political themes[35]. VADER's novelty stems from the way it handles brief and informal documents. Its lexicon was built in two stages: by crowdsourcing coding of informal vocabulary and subsequently by combining the assessments of several coders. Second, it goes beyond the bag of words approach by following a set of rules. For example, exclamation marks are assessed as a multiplier of sentiment with the same direction; or documents with all caps earn more intense sentiment scores. Finally, it reweights phrases like 'but' and 'however' that can shift the tone of a tweet[36].

VADER uses its lexicon to produce a weighted sum of all word scores, then normalizes the resulting measure between -1 and 1, eventually producing a compound sentiment score for each tweet. Positive sentiment is represented by higher scores,

33. As a more detailed list of which state sent how many tweets, see Appendix Figure 8
34. Hutto and Gilbert 2014.
35. Elbagir and Yang 2019; Endsuy 2021.
36. Bestvater and Monroe, forthcoming.

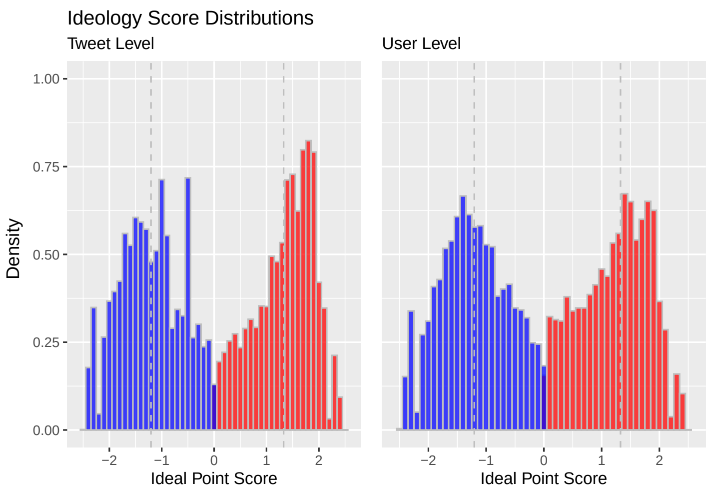

FIGURE 1. *Scores below 0 (liberals) are shown in blue, and scores above 0 (conservatives) were highlighted by red. Mean scores for each group is shown by the dotted lines.*

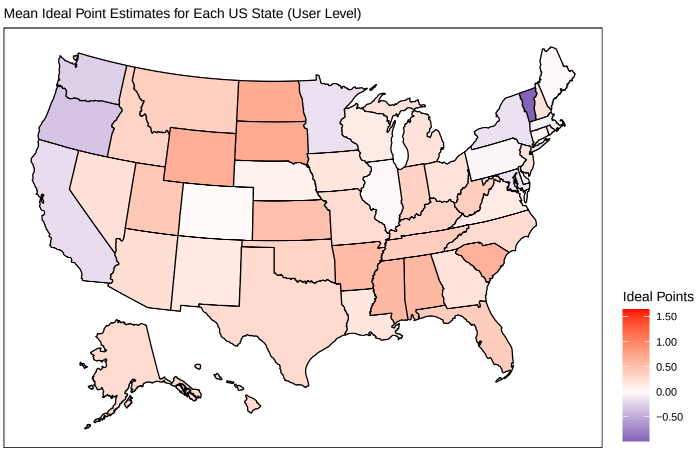

FIGURE 2. *The mean ideology scores for each state*

while lower scores represent negative sentiment. We implemented VADER both on raw and preprocessed text after removing mentions, links, and lemmatization. The algorithm produced similar results for both the cleaned and raw datasets. We proceeded with the raw data because VADER also analyzes components that are deleted by lemmatization, such as capital letters or punctuation. Figure 3 shows the distribution of sentiments by ideology at the tweet and user-level (tweet sentiment averages for each user). While we recognize that sentiment does not always imply political stance[37], it can nonetheless provide insight into whether people of various ideologies have similar reactions to a given topic.

After creating two key variables for our analysis, namely ideal point scores and sentiment scores, we applied structural topic modeling (STM) to explore what subtopics inside the withdrawal issue were discussed among Twitter's ideological circles. STM is an unsupervised text analysis method that uses a probabilistic Bayesian estimation method to uncover latent topics in a corpus. It follows a statistical rationale that assesses the likelihoods of keywords and concepts appearing together and derives topical meanings from those likelihoods. STM is a more advanced version of the popular Latent Dirichlet Allocation topic modeling algorithm (LDA). LDA determines documents' topics and words within topics in a probabilistic way, unlike the previous algorithms' deterministic approach. While LDA was formerly the most common method in text analysis, it has three main flaws[38]. Firstly, the topics in a given document are assumed to be independent of each other. In other words, topics do not inform other topics in the same document. Secondly, the distribution of words within a topic, i.e., topic content, is stationary. Put another way, words for a given topic are the same across all documents. Finally, topics are decided exclusively on the basis of the text, with no input from outside sources. The STM solves these three issues by allowing researchers to infer topic prevalence and content using contextual factors in prior distributions. It is also well suited for short documents such as tweets[39]. Another advantage of STM is that using these contextual variables from metadata as predictors, the researcher could apply a regression to estimate the proportion of each document having a particular topic.

For covariates in our model, we used author IDs (as the tweets from the same author could be considered together), time (month), state, author's follower count, author's tweet count, and author's ideology score. One drawback of structural topic modeling is that the number of topics must be specified when the model is run. We run multiple models with the number of topics from 4 to 81 to find the best model fit. We determined that the best number of topics for our corpus should be around 16 after considering numerous parameters such as held-out likelihood, residuals, semantic coherence, and exclusivity. More details on the model selection can be found in Appendix Figures 9, 10, 11. After running the model with 16 topics, we labeled the

37. Bestvater and Monroe, forthcoming.
38. Roberts et al. 2014.
39. Tvinnereim and Fløttum 2015; Curry and Fix 2019.

FIGURE 3. *Sentiment Distributions by Ideology. On average, conservative users sent more negative tweets on the Afghanistan withdrawal as shown by the red area.*

top ten topics as shown in Table 1, based on our inspection of most probable words and the most representative tweets for each topic.[40] Most topics appeared to have a clear semantic coherence[41]. An initial glance of the topics reveals that the most discussed themes were the plea for support for Afghanistan, the Biden administration's handling of the crisis, and the United States military failure after twenty years of fighting. A more detailed list of topics with more examples could be found in Appendix Table 3. After creating all necessary variables, as the paper's main results, we regressed sentiments and ideal point scores on topic proportions.

Finally, we also investigated the relationship between tweet sentiments and user ideology. Using ideal point scores of users as the outcome variable and the sentiment scores as the main predictor, we run four models, as shown in Table 2. We applied traditional simple OLS in the first two models to estimate sentiment scores on a continuous scale. For the third and fourth models, we applied logistic regression using re-coded ideology as binary (liberal and conservative). We also controlled different sets of variables among models.

40. For the most probable words for each topic, see Appendix Figure 13.
41. See the Appendix Figure 12 for a thorough comparison of topics based on their exclusivity and semantic coherence scores.

TABLE 1. *Labels and Examples for the Top 10 Topics*

Topic Num	Topic Name	Topic Prob.	Most Prob. Terms	Tweet Example
6	Pray & Call for Help for Afghan Ppl	0.137	peopl want can know need think help	If we out here saying pray for Afghanistan, let's really pray pray pray!!!!!Like really pray to God and ask Him that He move in ways that restore and protect those in suffering, those mourning, those in difficulty! God cares, God hears,God knows!Ask! Seek!Knock! He's there!
8	Biden's Handling of the Withdrawal	0.094	biden presid joe administr via blame call	The Biden administration is blaming President Trump for Afghanistan. I blame the Obama, Bush and Biden administration for the problems at the border and Afghanistan. Own up to your demented self Biden.
12	Military Failure	0.086	countri militari back fight forc give much	@LindseyGrahamSC Think of this. Pedo Joe has singlehandedly given the Taliban a well trained and equipped army, a well trained and equipped Air Force and a giant well equipped air base. He's a Lefty Loon Grifter's dream!
10	Fighting in Historical Context	0.081	year just time last got first watch	Well, compare to the last 20 years. What's even crazier is that we watched the USSR invade Afghanistan, stay there for 9 years, then leave. Then we did something pretty damn similar. And we were involved in the USSR in Afghanistan, just funding the opposition. Same ole shit.
13	News on Attacks	0.075	one say kill airport afghan soldier news	Open SmartNews and read ""Two 'high profile' ISIS targets in Afghanistan killed in US drone strike, Pentagon says"" here: https://t.co/o4IVIWTKKu \nTo read it on the web, tap here: https://t.co/cyfdIuVTYO
2	Abandoned American allies by POTUS	0.068	american potus mani still behind alli citizen	@POTUS Day 34 for the Americans U left behind in Afghanistan for the Taliban terrorist butchers. 38 CA school kids still there! #TalibanJoe #BidenDisaster
11	Plans on Withdrawal of Troops	0.065	troop withdraw even thing plan talk pull	America withdraws its troops and suddenly ya'll are okay with continuing to spend trillions of dollars to keep troops in Afghanistan and continue American imperialism.
3	US Security	0.061	take make govern state good look nation	@FroghWazhma Military government, close down all non security institutions, spend more budget on security. Let @AmrullahSaleh2 to take control of the Gov %100. Eradication of Taliban first step from gov jails. %100 control over media, like Qatar.
4	Afghan Women	0.052	now right women support world children seem	@RepMaxineWaters Hey big mouth! Haven't heard a peep from your so-called care for protecting women, for the women and girls of Afghanistan. Girls raped and tortured and married to older men. Women beaten and subjugated to men. Torture! AND, you care about horses.
9	Afghan Refugees	0.046	will come refuge famili work today servic	Love love love my football club: "Around 150 Afghan refugees treated to free tickets for Watford cup match" https://t.co/1IeoAuJsCz

Discussion

Our findings could be broadly divided into two categories. First, we will discuss how topics differ based on ideology and sentiment in the sections below. Second, we look at how sentiments and ideologies are linked when topics are disregarded. Finally, we examine the relationship between bot/spam accounts and the two ideologies.

To investigate whether there was political polarization on tweets along ideological lines, we estimated a regression of documents on the proportion of each document about a topic, controlling for several variables. The results can be seen in Figure 4. If, as Baum and Potter (2019) argues, people's opinions are more polarized as a result of Twitter's hyper fragmented nature, or if, as Kupchan and Trubowitz (2007) argues, foreign-policy polarization levels are similar to those in domestic politics, we should expect the majority of the topics discussed by the two ideological positions to differ significantly. However, as Figure 4 shows, we did not observe substantial variations in topic proportion estimates by ideology for the majority of the topics. This suggests that, for most topics, conservative and liberal Twitter users can coexist in the same conversation. However, a few divergent topics emerge as a result of ideological differences. Conservatives were more likely to tweet about Americans abandoning their Afghan partners and the Biden administration's withdrawal handling. Liberal users, on the other hand, were more inclined to post tweets on topics on the humanitarian side of the issue, such as Afghan women's predicament under the new Taliban regime, praying for help for Afghanistan, and fighting from a historical perspective. Overall we find that users with different ideological positions could still meet in the same discussions for most topics. However, even if these users posted tweets on the same topic, this is still not enough to prove they were on the same side. To assess this, we investigated how tweet sentiments estimated topic proportions.

When the conservatives and liberals meet in the same subtopics, how similar their reactions were? We evaluated how successful sentiments were in estimating the topics. Perhaps unsurprisingly, the Figure 5 shows that more 'humanitarian' topics, such as calling for help for Afghans and the future of Afghan women, have higher overall positivity, whereas topics that seek to assign blame, such as Biden's handling of the situation or abandoned American allies, have a more negative sentiment. Most topics, however, converge in the center, indicating that they were not significant predictors of topics. This demonstrates that when conservative and liberal users coexist on the same issue, there is no discernible difference in their sentiments.

After investigating how ideology and sentiment estimate topic proportions, our discussion now turns to the association between the first two. Can ideology be predicted with sentiments? As Table 2 and the linear relation in Figure 6 show, the sentiment is negatively correlated with ideal points, i.e., being conservative meant the increased probability of tweet negativity. These results are maybe not surprising in the context of Afghanistan withdrawal, considering that conservatives were on the opposing side, criticizing the Biden administration's process management. Our results align with the recent psychology literature, which suggests that political liberals are generally happier than conservatives, and they are more likely to use positive phrases,

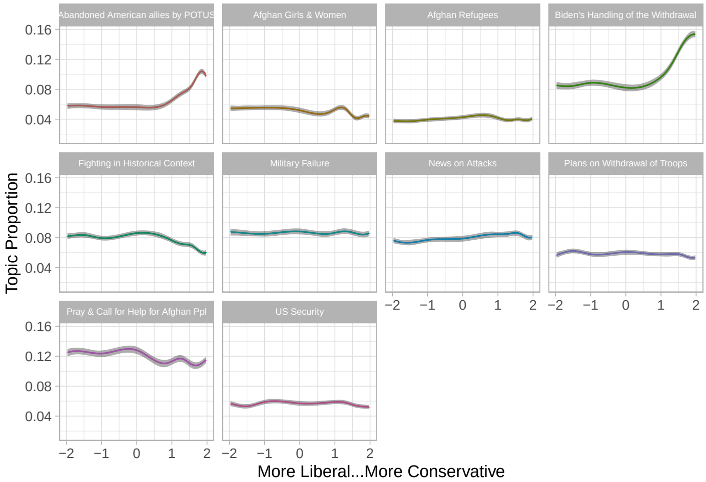

FIGURE 4. *Regressions estimates for the most prevalent ten topics of ideal point scores. 95 percent confidence intervals are shown by the dark areas around the lines.*

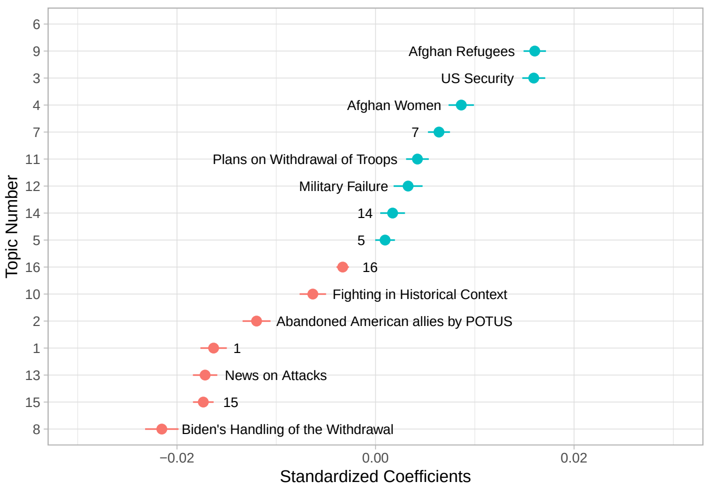

FIGURE 5. *Regression Estimates of Sentiments for Topic Proportions. The sentiments were recoded as positive and negative before running the model, then regressed on the topic proportion for each topic. Positive coefficients are colored by blue.*

expressing positive sentiments[42]. Their study finds consistent results across various samples, including online survey takers, U.S. politicians, Twitter and LinkedIn users.

TABLE 2. *Regression Results for Ideology*

	Dependent Variables			
	Ideology (Cont.)		Ideology (Conservative=1)	
	OLS		*logistic*	
	(1)	(2)	(3)	(4)
Sentiment Score	−0.120	−0.108	−0.124	−0.121
	(0.009)	(0.009)	(0.014)	(0.014)
Bot Score		0.512		0.607
		(0.022)		(0.036)
Like Count		−0.000		−0.000
		(0.000)		(0.000)
Author's Follower Count		−0.000		−0.000
		(0.000)		(0.000)
Author's Tweet Count		−0.000		−0.000
		(0.000)		(0.000)
Author Verified		0.186		0.734
		(0.029)		(0.050)
Constant	0.342	0.334	0.462	0.488
	(0.005)	(0.008)	(0.008)	(0.012)
Observations	66,288	66,191	66,288	66,191
Log Likelihood			−44,060.760	−43,153.910
Akaike Inf. Crit.			88,125.520	86,321.830
Residual Std. Error	1.359 (df = 66286)	1.342 (df = 66184)		
F Statistic	176.076 (df = 1; 66286)	319.844 (df = 6; 66184)		

Finally, our bot analysis revealed that about 14% of the withdrawal-related tweets were not genuine. Such a high number implies that even discussions on foreign matters could be easily distorted because of bot accounts. One might wonder how the bots were associated with ideologies. Only 37% of the tweets labeled as 'bots' belonged to the liberal users, while 63% belonged to the conservative accounts. Bot accounts were shown to be strongly associated with higher ideology scores (being more conservative), as seen in Table 2. Our findings are in line with those of the developer of the R package 'tweetbotornot'[43]. After running several models, he found that being conservative was a significant predictor in estimating the probability of being a bot account on Twitter.

42. Wojcik et al. 2015.
43. Kearney 2021.

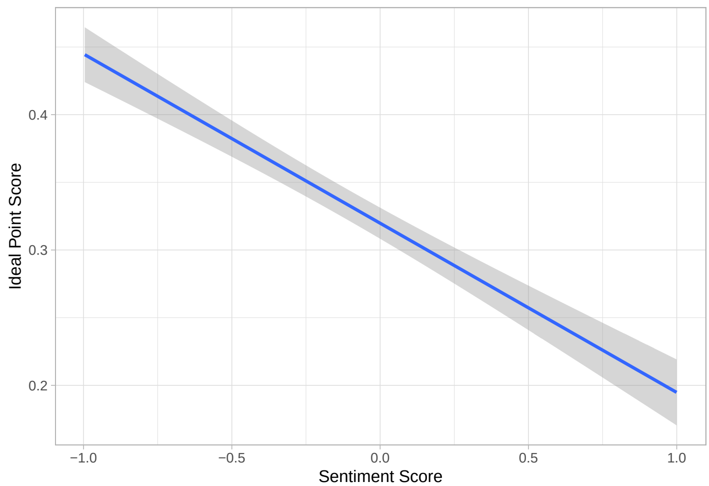

FIGURE 6. *Change of Sentiment Scores by Ideology. Higher ideal point scores refer to more conservatism.*

Conclusion

Although our findings have important implications for the polarization literature, we caution against extrapolating our results to the entire population since Twitter is a self-selected sub-sample of Americans. As previously stated, some voices on Twitter are less likely to be heard due to a variety of sociodemographic factors[44]. We avoided making strong causal assertions throughout the study because of this, as well as the fact that causal inference remains one of the most challenging tasks in natural language processing research[45]. We also did not focus on one ideological group's online behavior; instead, we compared conservatives and liberals relatively. Hence, even if the groups are not representative samples from their respective real-world populations, we assumed that the groups must have been self-selected from each group through similar criteria.

Drawing from foreign-policy polarization and Twitter polarization research, we argued that political polarization along ideological lines might shift depending on the foreign event. Even with that event, individuals could still polarize on some subtopics but not on others. We first estimated bot probabilities, sentiment values, and ideal point scores for a novel Twitter data on American users' reactions to Afghanistan pullout. Then, using structural topic modeling, we analyzed what topics dominated the discussion. We found that liberal users tweeted more on praying for Afghanistan and

44. Hargittai 2020.
45. Feder et al. 2021.

on Afghan women's future, while conservative users were more interested in Biden's handling of the withdrawal and on leaving American allies in the country. Our findings support the more nuanced viewpoint that we cannot draw broad generalizations about an overarching trend in foreign-policy polarization. We also investigated the relationship among sentiments, ideology, and bot accounts, and we found that both negative sentiments and bot accounts were associated with conservative users.

Appendix

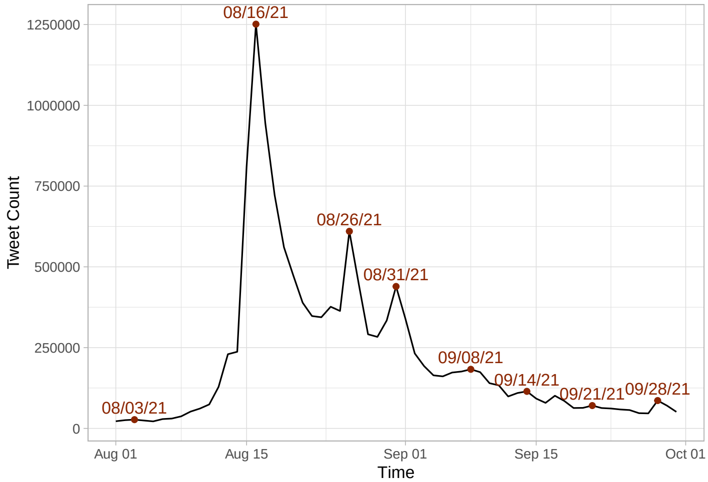

FIGURE 7. *Tweet counts on Afghanistan withdrawal by month. Only months from August 1, 2021 to October 1, 2021 are included here as the count levels for the remaining months are low. Dates in red show the important break-points.*

Model Selection for Structural Topic Modeling

In topic modeling, the most critical hyperparameter when running a model is the number of topics, k. Hence, we would want to compare models with different values of k and choose the most optimal number. Figure 9 shows the diagnostics with the number of topics from 4 to 81. Here, we aim to maximize held-out likelihood while minimizing the residuals. Models with k higher than 40 have quite low held-out likelihood; therefore, we disregard any number above 40. We also want to achieve higher semantic coherence, but it is relatively easier to do so with low k. Hence, as suggested by Roberts et al. (2014), we also take exclusivity into account. Figure @ref(fig: trade-off) provides a closer look at the trade-off between semantic coherence and exclusivity. After visually inspecting this trade-off, we determined that the optimal number of topics is around 16 because semantic coherence is substantially stronger at that point, and exclusivity is not as high as it is at other numbers.

After choosing the k to be 16, we evaluated multiple model runs based on different initialization settings to see if the model performance changes considerably based on the initial values. We utilized the `many_models` function in `stmprinter` package to accomplish this[46], which took 66.3 hours on American University's 24-core high-

46. Johannesson 2021.

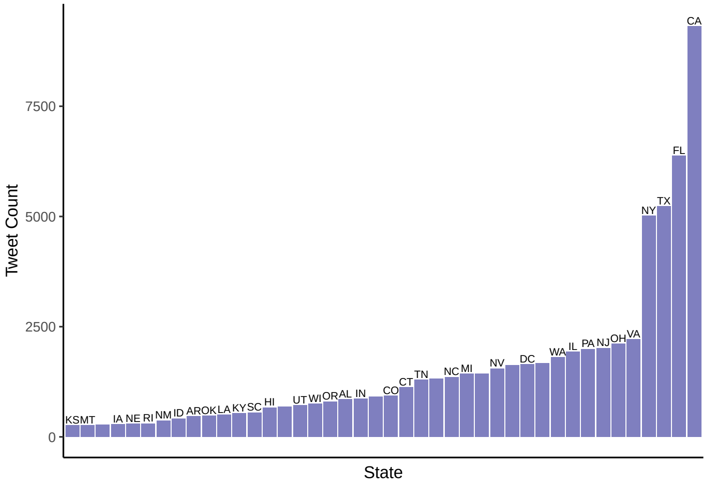

FIGURE 8. *Tweet Counts by State. While California sent the most tweets on Afghanistan withdrawal by far, some states did not really engage in the issue.*

performance computer with an average memory use of 17GB. We found no significant differences in exclusivity and semantic coherence scores across models based on their initial priors, as shown in Figure 11. Therefore, instead of using randomly selected initialization numbers, we proceeded with the spectral initialization as suggested by Roberts et al. (2014) with 16 topics. The model converged in 49 iterations.

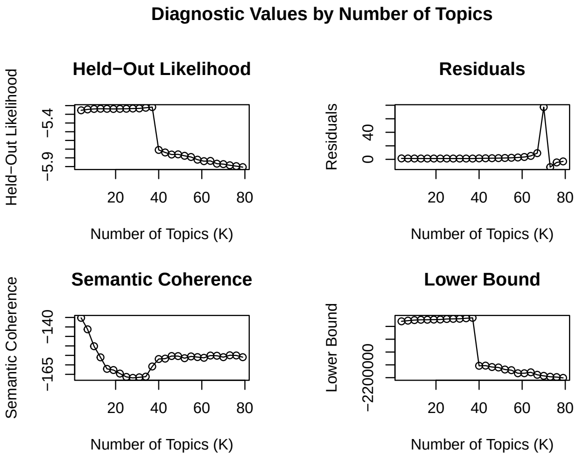

FIGURE 9. *Model diagnostics by number of topics.*

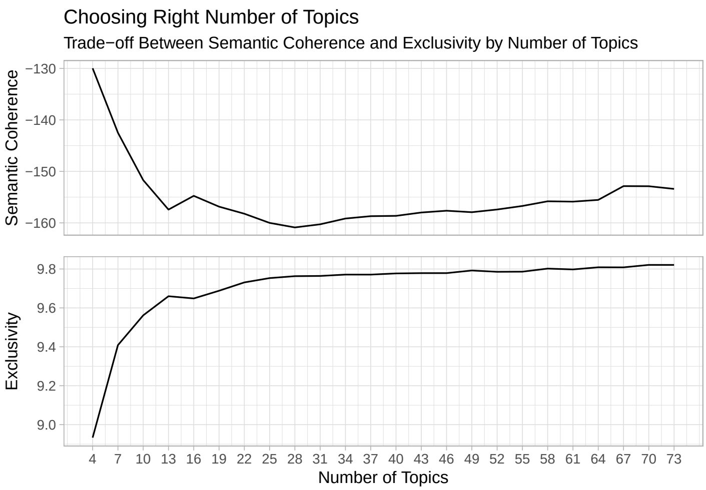

FIGURE 10. *The model run for each of these different number of topics, and the results show the tradeoff between exclusivity and tradeoff for each number of topics.*

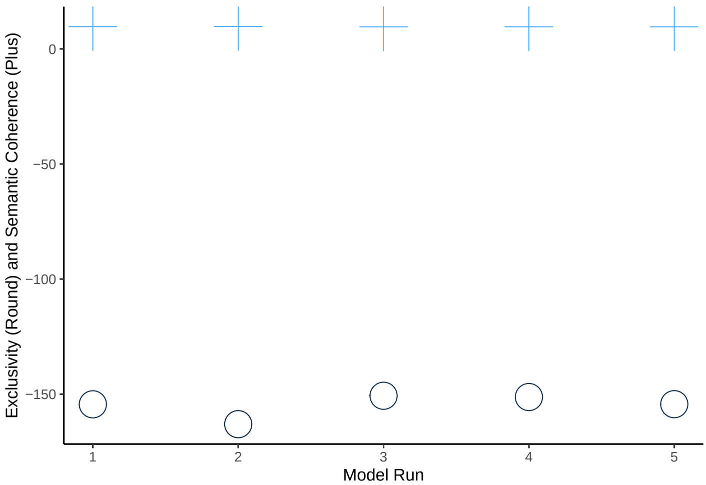

FIGURE 11. *Exclusivity and Semantic Coherence scores among different runs when number of topics is 16.*

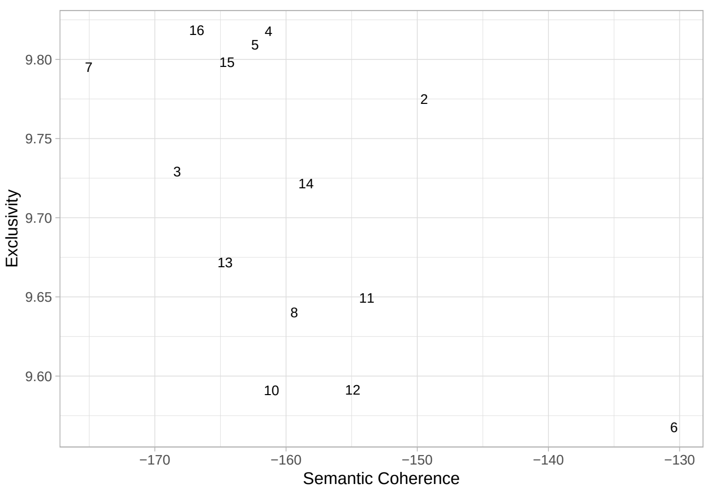

FIGURE 12. *Semantic Coherence and Exclusivity Scores for Each Topic. The scores were calculated for the selected model, in which the number of topics is 16*

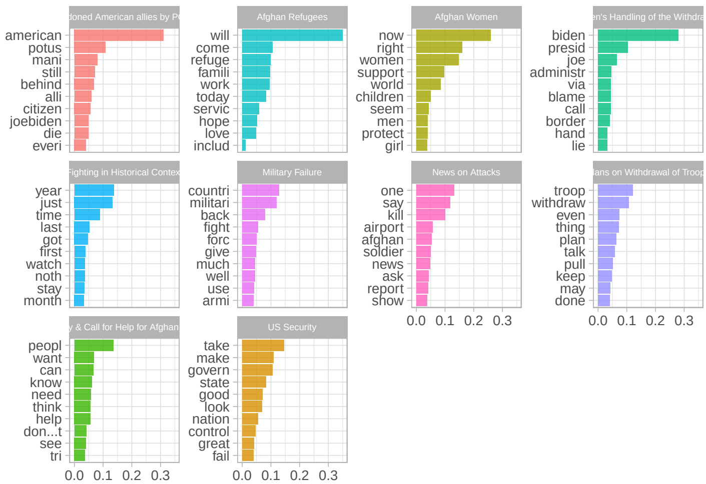

FIGURE 13. *The words with the highest probability of selection for each topic.*

TABLE 3. *The Most Representative Tweets for the Top 10 Topics*

Topic Name	Example 1	Example 2	Example 3	Example 4	Example 5
Pray & Call for Help for Afghan Ppl	If we out here saying pray for Afghanistan, let's really pray pray pray!!!!!Like really pray to God and ask Him that He move in ways that restore and protect those in suffering, those mourning, those in difficulty! God cares, God hears,God knows!Ask! Seek!Knock! He's there!	@GiancarloC1985 If the people there really wanted what we were offering, the military wouldn't have laid down their guns and joined with the Taliban. I'm sure a good number of people totally want democracy, but it needs to be a majority wanting it for it to be effectual.	@KSAnimalRescue @BorisJohnson @DailyMailUK @SkyNews @DominicRaab @puppyrescuemis1 @PressSec @FoxNews @BillFOXLA HELP please! jen u said in ur briefing to a reporter, if u know someone needing help in Kabul to get u their info. . . this woman, her staff, & animals need help! . . . all paperwork is in order EXCEPT NEED A LANDING PERMIT. . . PLS HELP!	@natiqmalikzada @JackPosobiec Makes sense? Taliban acquires a city and destroys it? Honestly. You can pray all you want won't but just not going to change. I pray for the innocent who just want to be free. Can ANY OF US IMAGINE being a U.S. soldier? I pray for them. I pray for all of you too. God Bless!\n	Same people that don't want to help immigrants from South America all of a sudden want to open the flood gates for Afghan Muslims? \nNot really, they just want to find something they can criticize Joe Biden about. \n#GOPHypocrisy https://t.co/drl8dJHuYA
Biden's Handling of the Withdrawal	The Biden administration is blaming President Trump for Afghanistan. I blame the Obama, Bush and Biden administration for the problems at the border and Afghanistan. Own up to your demented self Biden.	Everybody has had their fill of the commies Democrats and Biden mask Covid Afghan all the failures that's the reason for the fuck joe Biden chanting	I'm sick and tired of the body administration and the Democrats blaming the debacle of Afghanistan on President Trump President Biden administration has destroyed anything good that President Trump has done so why are they blaming the debacle of Afghanistan on President Trump	French President Emmanuel Macron Lectures Joe Biden on 'Moral Responsibility' in Afghanistan https://t.co/4V8vz13tw9 via @BreitbartNews	Rep. Markwayne Mullin: Biden admin lying about Afghanistan, president 'has blood on his hands'\nWr have reached the level of the question now is how to tell when Biden is NOT LYING! He now lies about his lies. \n\nhttps://t.co/q9v0EiijJ2
Military Failure	@LindseyGrahamSC Think of this. Pedo Joe has singlehandedly given the Taliban a well trained and equipped army, a well trained and equipped Air Force and a giant well equipped air base. He's a Lefty Loon Grifter's dream!	@bryanrbeal That was weapons given to the afghan army who didn't use it to fight the Taliban and instead gave up	@Toxik_431 @CreamMachine326 @JuliaManch @benshapiro Imagine the Taliban is coming. What would you an American do? Fight! \n\nUSA spent trillions on training an Afghan army for 20 YEARS! They had 325k strong. 4:1 numbers, Air Force, Blackhawks, billions in military equip. They didn't even fire a shot for their Capital! No FIGHT!	@Styo28183449 @BuckeyeinDC @Baconside @LauraJedeed Who was paying the Afghan army? Once it became clear the money would stop where was the incentive to fight against the Taliban?The Afghan army when given a choice to fight the Taliban or put their guns down almost always turned tail and ran. This was about money not beliefs	@KwikWarren Honestly, it looks like all along (20 years to be exact) the US military was training the Taliban and strategically placing military equipment across the country for them, just in case they'll need it to fight the 'bad Taliban'. Well well well!
Fighting in Historical Context	Well, compare to the last 20 years. What's even crazier is that we watched the USSR invade Afghanistan, stay there for 9 years, then leave. Then we did something pretty damn similar. And we were involved in the USSR in Afghanistan, just funding the opposition. Same ole shit.	Last time we "pulled out of Afghanistan" we got ISIS and had to act to a complicated crisis. Come on @POTUS what's the last 20 years mean to you	$3.5 Trillion over 10 years is less than we spent in Afghanistan the last ten years, @JoeManchinWV.	@JohnCornyn Yesterday? Really? You've been in office as long as we've been In Afghanistan. This is the first time you've noticed a problem?	Just spoke with 4 veterans who served in Afghanistan who say after 20 years of fighting, it only took a matter of weeks for all they've sacrificed to fall apart. Full story soon. https://t.co/DpS8EsQByO
News on Attacks	Open SmartNews and read ""Two 'high profile' ISIS targets in Afghanistan killed in US drone strike, Pentagon says"" here: https://t.co/o4IVIWTKKu \nTo read it on the web, tap here: https://t.co/cyfdIuVTYO	Open SmartNews and read ""Afghanistan news: 17 reported dead in celebratory gunfire as Taliban claim to have taken Panjshir"" here: https://t.co/rfzeau1ZH8 \nTo read it on the web, tap here: https://t.co/WVKO5Ygj3R	Open SmartNews and read ""Taliban show off captured, blindfolded ISIS terror suspect"" here: https://t.co/YppH8FAqpy \nTo read it on the web, tap here: https://t.co/IONxT5RFhN	Open SmartNews and read ""Taliban are reportedly beating Afghans for wearing western clothes"" here: https://t.co/MM7N8SozLP \nTo read it on the web, tap here: https://t.co/cTOdC1aWEB	BREAKINGNEWS UPDATE KABUL AIRPORT BOMBING - Two explosions at the Kabul Airport kills more than a dozen people. Pentagon officials say U.S. service members and Afghan civilians were among the casualties\n\nhttps://t.co/dUzAbW62n2
Abandoned American allies by POTUS	@POTUS Day 34 for the Americans U left behind in Afghanistan for the Taliban terrorist butchers. 38 CA school kids still there! #TalibanJoe #BidenDisaster	@joebiden @potus @PressSec @PentagonPressSec How many US Citizens are STILL #standed and being held #hostage in #Afghanistan ?? https://t.co/wbpD3Zs6oX	@POTUS Day 2 of Americans & Afghan allies left behind by a weak, feckless President. #NoOneLeftBehind #TalibanJoe	Why is anyone surprised @JoeBiden abandoned his dog Major? The @POTUS abandoned how many Americans in Afghanistan? What's a dog to him.	@POTUS Day 42 for the Americans U left behind in Afghanistan for the Taliban terrorist butchers. #TalibanJoe #OpenBordersJoe
Plans on Withdrawal of Troops	America withdraws its troops and suddenly ya'll are okay with continuing to spend trillions of dollars to keep troops in Afghanistan and continue American imperialism.	2 of 2\n"Getting out of Afghanistan is a wonderful and positive thing to do. I planned to withdraw on May 1st, and we should keep as close to that schedule as possible."\n@EArosemenaM @YoouurrMama @Hol_Shayer @JoannieRose78 @PRus51	""The US was going to pull out regardless, for political and economic reasons. Blame Biden for a bungled withdrawal, not for the withdrawal itself. Trump was even more eager to withdraw."" https://t.co/gktVppAkvz	Then he might want to recall this statement\n\n""Getting out of Afghanistan is a wonderful and positive thing to do. I planned to withdraw on May 1st, and we should keep as close to that schedule as possible."" -Donald Trump https://t.co/24iNzhxlRz	I accidentally retweeted a Pres. Trump statement from April praising HIS decision to pull out of Afg. Remember he invited the Taliban to the talks. Bidens mistake was to keep that plan but his withdrawal of troops has been a disaster. Maybe neither should have trusted them.
US Security	@FroghWazhma Military government, close down all non security institutions, spend more budget on security. Let @AmrullahSaleh2 to take control of the Gov %100. Eradication of Taliban first step from gov jails. %100 control over media, like Qatar.	The government of Afghanistan appeared to be expanding and solidifying its control beyond the urban areas and into remote regions. It looked like stability, civil authority, and dependable governance could take hold.\n\nWhen I returned to Afghanistan in 2015 I was concerned.	@tedcruz If we abandon those that helped our soldiers in Afghanistan.\n\nThen we have diminished the credibility of the United States and its government. It was never the intention for the United States to be controlled by those who make the largest donations.	By powers vest by the Constitution of the United States as President Commander and Chief of the United States Dwayne Antonio Riojas do here by VETO The Afghanistan \n\nHarris makes rare recess appearance to help pass Afghanistan evacuee bill https://t.co/QnOloxVa17 via @politico	Suggestion: start Military gov, close down all non security institutions, spend more budget on security. Let @AmrullahSaleh2 to take control of the Gov %100, or at least security cabinet,Eradication of Taliban first step from gov jails. %100 control over media, like Qatar gov.
Afghan Women	@RepMaxineWaters Hey big mouth! Haven't heard a peep from your so-called care for protecting women, for the women and girls of Afghanistan. Girls raped and tortured and married to older men. Women beaten and subjugated to men. Torture! AND, you care about horses.	@RichardEngel Are the Afghanistan men coming out? No? Perhaps the majority of men are with the Taliban's position on women's rights. Women all over the world face hostility and violence...USA is no exception.	In normal life I distain violence, but what the Afghan women will most likely suffer is not normal but the roots of evil. I encourage and I pray that the women take up arms to protect their rights since it appears that the men won't. https://t.co/ZV4Xxx8u8b	Today is a bad day for the rights of women and children. Women's rights are human rights and those right cannot flourish under a Taliban government.	This is a return to Taliban's draconian rule of the 90s denying men and women basic fundamental rights. If this wasn't acceptable to the civilized world back then why should it be now? #TalibanHaveNotChanged. https://t.co/7Ewi04ukKp
Afghan Refugees	Love love love my football club: "Around 150 Afghan refugees treated to free tickets for Watford cup match" https://t.co/1IeoAuJsCz	Have you noticed @benshapiro that Taliban local Mayors sound like NYC's @BilldeBlasio?\n\n"Workers will be encouraged to come back to work (vax) & we'll be nice about it."\n\n*1 week goes by*\n\n"All will come back to work or be beheaded & your family starved for your noncompliance."	Sacramento will always be a place that welcomes everyone to come & live. Thankful we have a group of advocates working w/ our Afghan refugees - who come seeking safety & shelter - w/ services they need to transition into life here in Sac. https://t.co/E0KMOA7WoS	Will #Syracuse become a Safe City for Afghan refugees and immigrants? I sure hope so. I hope @BenWalsh44 @SenGillibrand @SenSchumer are working towards this.	To the families of those US Marines who died or were wounded today in Kabul Afghanistan, my family and I salute you. We will pray for you. We are deeply grateful for the service of your loved ones and we are stricken by your loss. We are so sorry.

Supplementary Material

Supplementary materials for this article is available at <https://doi.org/10.1017/Sxxx xxxxxx>.

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