American Twitter users have ideological differences of opinion about the War in Ukraine

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Abstract

Though ideological differences have long been a ubiquitous feature of American politics, the rise of online news and social media has exacerbated divisions between groups. While existing research has documented how political preferences manifest online, relatively few studies have considered whether ideological divisions extend to discussions of foreign policy. We examine this question by analyzing nearly 2 million tweets about the war in Ukraine posted by Americans during the opening stages of the Russian invasion. We first categorize each tweet according to the user's ideological leanings estimated by the network of political accounts they follow. Then, we apply a natural language processing model specifically designed for short texts to classify the tweets into clusters that we hand code into substantive topics. We find that the topic distributions of conservative, moderate, and liberal users are substantively and statistically different. We further find that conservatives are more likely to spread some form of misinformation and that liberals are more likely to express support for Ukraine. Our paper concludes with a discussion of the implications of our findings for the conduct of U.S. foreign policy.

Keywords: political preferences, ideological differences, foreign policy, ideology, social media, war in Ukraine

Word Count: 4,231

Introduction

Ideological differences of opinion are a ubiquitous feature of U.S. politics (*1–7*). In contemporary politics, Americans are deeply divided on a host of domestic issues including policing, immigration, and COVID-19 (*8, 9*). Recent studies have found that these divisions also extend to foreign policy issues. For example, Americans disagree over nuclear weapons, climate change, the use of force, human rights, and multilateralism (*10–14*). Indeed, domestic political preferences appear to be remarkably resilient concerning foreign policy, among both elites and publics (*15–18*).

Prior research has attributed this domestic divide to the sharing of information within selective social networks that connect users with like-minded others (*19, 20*). Social media platforms facilitate the process of sorting users into ideological networks that limit individuals' exposure to alternative political views. The increase in social media use has thus amplified concerns about divisions in the United States (*21*). However, most of these studies focus on political differences over domestic, not foreign, policy. Despite the abundance of evidence that domestic political preferences carry over into the foreign policy realm, we know surprisingly little about how people engage with foreign policy issues on social media platforms. Given that a majority of Americans consume, access, and discuss politics online, including on social media (*22, 23*), it is particularly pressing to understand how these dynamics unfold (*24, 25*).

We investigate public reactions on social media in response to the war in Ukraine, a highly salient political issue that is nonetheless undeniably international in nature. We examine an original dataset of nearly 2 million Twitter posts (known as "tweets") to trace how political discourse about Ukraine spread within ideological social networks on social media. Our sample consists of tweets about the war in Ukraine posted during the opening days of the invasion

(February 24-28, 2022), before political attitudes hardened. Of the universe of tweets posted during this period, we identify those that include one of our pre-defined keywords (see the "Materials and Methods" section). We subsequently categorize each tweet according to the user's ideology—conservative, liberal, or moderate—by looking at the network of political users that each individual follows. We classify users in this way to explore whether individuals sharing political information within different social networks engage in divergent political discussions. Then, we apply a natural language processing (NLP) model tailored for short texts (*26*) to classify our large collection of social media posts. Applied to our data, the NLP model groups together tweets with similar words and meanings into clusters to facilitate analysis. The model assumes that semantically related tweets indicate an underlying topic. Finally, we hand-code the content of each cluster into a set of aggregate substantive topics.

The war in Ukraine is an especially interesting case because American elected officials have remained largely unified in their response to the invasion. In his March 1st, 2022 State of the Union speech, President Joe Biden made this point explicit: "[Russian President Vladimir Putin] thought he could divide us at home, in this chamber and in this nation...But Putin was wrong. We are ready. We are united, and that's what we did. We stayed united." Members of Congress from both sides of the aisle sported the blue and yellow colors of the Ukrainian flag in support (*27*).

Yet the issue seems more divisive for American citizens. American liberals, conservatives, and moderates ostensibly think of Russia, Ukraine, and the conflict in fundamentally different terms. At its core is former President Donald Trump's public esteem for Putin. For example, the day after the invasion began, Trump praised Putin as a "very savvy" leader who made a "genius" move. In a February 26–March 1, 2022 Economist/YouGov poll of 1,500 Americans, only 54% of conservatives reported having a "very unfavorable" view of Putin, compared to

70% of liberals and 62% of moderates. These views also translate to policy evaluations: only 19% of conservatives surveyed in this poll approved of the Biden administration's handling of the Ukraine crisis, a remarkably low share compared to liberals (68%) and moderates (49%).

Materials and Methods

Data Collection

We collect the universe of tweets discussing the war in Ukraine using a broad keyword search via the Twitter Application Programming Interface (API). We download tweets posted during February 24–28, 2022, and contain at least one keyword (Ukraine, Ukraina, Ukrainian, Ukrainians, Kyiv, or Kiev), resulting in about 6.5 million tweets collected. We chose this period because it marks the first 5 days of the war, including Russia's initial invasion. This strategy allows us to examine public responses to the war as the opinions were still forming. We pre-process the text of the tweets by removing hyperlinks, mentions, extra space, and new lines. Then, we use *cld3*, a language identification package released by Google to detect the language of tweets and select only American English tweets. Using this method, we retain an American English corpus containing about 4.4 million tweets.

Our sample is likely broadly representative of American political discourse on Twitter for three reasons. First, we use American English to refine our sample. Individuals who post in American English participate in the broader American online political discourse on a given subject, even if they are not voters. Second, by limiting our analysis to those accounts that post in American English *and* follow at least one political account, we are limiting our sample to users that are at the very least participating in the political conversations about Ukraine, even if they are not doing so on an active or permanent basis. Finally, as a robustness check, we download and analyze the self-reported geographic location of all the tweets in our sample. 0.06% of our sample (2,648 Tweets)—a tiny fraction of our overall sample—did not originate in the United States, according to this user-reported metric. However, we still retain these users because, as discussed, these individuals may still participate in relevant American political discourse, even if they are not located in America. Some of these users may be traveling abroad overseas. Others may be living oversees permanently. Indeed, there are nearly 3 million eligible American voters living abroad. Regardless, we keep these tweets in the sample because the content of the tweet was a part of the broader political conversation we are interested in analyzing.

As a further validation check of whether these accounts belong to Americans or not, we fit a structural topic model on a random sample of tweets included in our in the main analysis (in sample) and excluded (out of sample). We find that in-sample tweets have a higher proportion of topics related to American politics and domestic concerns than out-sample tweets. We report the full results of the validation in the SI.

Measuring User Ideology

Next, we estimate the political leaning of each tweet by estimating the ideology of the user who posted it. Each tweet in our sample contains meta information that includes usernames. We estimate the political ideology of Twitter users based on who they follow. We begin by creating a list of 75 conservative and 75 liberal media accounts, including political commentators, talk show hosts, and journalists. We limit this list to popular accounts with a blue checkmark verification status on Twitter with more than 100,000 but fewer than 1 million followers. The data collection took place before the Twitter policy change that made the blue checkmark purchasable. This restriction ensures that our list contains mainstream accounts with clear ideologies. We evaluate the ideology of users in our data by matching the number of media accounts they follow and taking the difference between the number of conservative- and liberal-leaning accounts they follow. Formally, we define a user's partisan score as $\frac{L-C}{L+C}$, where L and C represent the number of liberal- or conservative-leaning media accounts they follow.

We classify users with a score of less than -0.5 as conservative, and those greater than 0.5 as liberal. We consider users with scores between -0.5 and 0.5 as moderate. We then connect each tweet to the user's ideology and retain only tweets for which we could identify the users' ideology. This process gives us 1.8 million tweets (almost half of the English corpus) that we use in the main analysis. Because the list of media accounts are U.S. based, users who follow them and thus are included in our analysis also are likely to be Americans.

We validate this measure in three ways, which we report in full in the Appendix. To begin with, we collect elected US officials' Twitter handles and use our list of media accounts to estimate their party affiliations. Assuming that Republicans are conservative and Democrats are liberal, we find that elected officials' party affiliations perfectly match the ideological types of the news accounts they follow. Democratic officials follow more liberal-leaning accounts than conservative-leaning accounts; Republican officials behave the opposite.

Next, we download the universe of tweets that include one of two ideological salient hashtags during the run-up to the 2022 U.S. midterm elections (January-November 2022): (1) #voteprochoice, a liberal hashtag used by liberals to encourage fellow liberals to vote for pro-choice candidates in the 2022 midterm elections; and (2) #voteprolife, a conservative hashtag used by conservatives to encouraging fellow conservatives to vote for pro-life candidates in the 2022 midterm elections. These hashtags focus on an ideologically salient issue in a costly way by using the word "vote." A conservative ideologue, for example, would be reticent to use the hashtag #voteprochoice since it denotes electoral support for a liberal position. We estimate

Table 1: Description of the Tweets in the Dataset

Group	Users	Median Tweet	Max Tweet	Min Tweet	Total Tweets
Conservative	204,688 (38.6%)	2	828	1	707,351 (37.9%)
Moderate	34,147 (6.4%)	2	631	1	149,847 (8.0%)
Liberal	291,989 (55.0%)	1	2,044	1	1006,935 (54.0%)
Total	530,824				1,864,133

the ideology of each tweet that either hashtag using the method we outline in the paper. This validation shows us that our measure performs as expected. Of the 14,313 tweets that use the #voteprochoice hashtag, our measure can identify the ideology of almost 60% of tweets. Among them, 8,157 tweets (97.9%) are by accounts coded as liberal. Similarly, of the 5,134 tweets that use the #voteprolife hashtag, our measure can identify the ideology of about 50% of tweets. Among them, 2,253 tweets (94.6%) are by accounts that code as conservative.

Finally, we also conduct a survey on Amazon MTurk to validate our measurement strategy. In the survey, we collect information on subjects' political participation and Twitter usernames. This data shows that subjects' voting records and ideologies are correlated with the types of news accounts they follow on social media. Subjects who voted for Biden in 2020 or defined themselves as Democrats usually follow more liberal-leaning accounts than conservative-leaning accounts on our list. We present the results of this survey in greater detail in Appendix B.

Our final sample contains 530,824 users and a corpus of 1,864,133 tweets. Of these, 38% of the tweets were posted by conservative-leaning accounts, 54% by liberals, and 8% by moderates. Table 1 reports summary statistics of our dataset. The median conservative and moderate user in our sample tweeted twice while the median liberal user tweeted once. The most active conservative user posted 828 tweets, the most active moderate user 631 times, and the most active liberal user 2,044 times.

Clustering Tweets and Aggregate Topic Labeling

We apply Top2Vec, an unsupervised clustering algorithm, to classify our large collection of social media posts (*26*). This method is especially well suited to analyzing short political texts (*28*). Compared to other topic modeling methods like Latent Dirichlet Allocation (*29*), our method does not require pre-determination of the number of topics or tokenization and stemming of the documents. Instead, the model retains the order of words when learning fixed-length distributed vector representations of documents (*30*) with neural networks. When the learning is done, documents that are semantically similar are supposed to be close in the vector space. The model assumes that semantically similar documents indicate an underlying topic. Therefore, it maps these document vectors to a lower-dimensional space using Uniform Manifold Approximation and Projection (*31*) and automatically find dense areas in that space using a Hierarchical Density-Based Clustering technique (*32*). Documents in the same dense areas are assigned to the same cluster, resulting in 6,171 clusters of tweets.

In order to facilitate further analysis, we aggregate the clusters into 7 meaningful categories, which we call substantive topics: "anti-media," "domestic politics," "foreign policy," "misinformation," "news," "Russia discourse," and "Ukraine Support." For example, tweets using words such as "lord," "amen," "Jesus," and "God" were grouped together, and upon further analysis, it was determined that such tweets were generally sent by people expressing their sympathy and support for Ukraine.

We implemented the following procedure of aggregate topic labeling and validation. First, We review tweets from the 100 largest clusters to identify qualitatively the 7 substantive topics. We describe our coding protocol for these categories in full detail in Appendix E. Second, we train two RAs to aggregate all clusters into substantive topics. Each tweet has a matching score indicating how far it is from the center of its assigned cluster. The higher the score, the more representative the tweet is of the whole group. They read the ten most representative tweets from each cluster and determine which category that topic belongs to. Third, if none of the categories is applicable, we exclude that cluster from our analysis. This results in dropping about 34% of the tweets from the substantive topic analysis. Fourth, We compare two RAs' labels and retain those they both agree on. Fifth, for clusters for which two RAs choose different labels, the three authors code them again and adopt the topic coding a majority of the authors agree upon. Finally, since it indicates valence, we validate the Ukraine support measure by hand-coding 500 randomly selected tweets of those our NLP model classified as supportive of Ukraine. We find that our NLP model accurately predicted the valence of 90.8% of the tweets.

Hypotheses

Our main research hypotheses evaluate whether social media users have different political conversations about the war in Ukraine within their respective ideological social networks. Our null hypothesis is that there are no differences across ideological groups. Given the nature of political preferences and partisan divisions in American politics, our first alternative hypothesis is that we expect to find that liberals and conservatives have different discussions about the same international issue (H1). That is, the general distribution of topics discussed related to the war in Ukraine will differ between liberal and conservative twitter users. In addition to examining users with clear ideological leanings, we examine how moderates respond. Recent research shows that a large portion of the American public has genuinely centrist views that make them political moderates (*33*). These findings suggest that moderates discuss different aspects of a given international issue than conservatives (H2a) or liberals (H2b) would. As applied to our case, we would expect moderate twitter users to post about a different general distribution of topics broadly related to the war in Ukraine than either conservatives or liberals.

Next, we consider the specific substantive content of social media discourse. First, we look at the sharing of misinformation within ideological networks (*34*). Recent work shows that conservatives are more likely than liberals to spread false or misleading news on social media (*35–37*). We therefore expect conservatives to be more likely to share misinformation about the war in Ukraine (H3). Finally, we investigate whether support for Ukraine differed according to users' ideological leanings. Past research has found that liberals are more supportive of international allies, humanitarian intervention, and foreign aid than conservatives (*12, 16, 38*). Although Republican elected officials joined Democrats in condemning the Russian invasion, some prominent conservative voices and media outlets offered more ambiguous positions. And so, we hypothesize that liberals are more likely than conservatives to express support for Ukraine (H4).

Results

In line with the main hypothesis, we find that liberals, moderates, and conservatives post about different topics related to the War in Ukraine. Table 2 lists the five most frequently discussed topic clusters of tweets by ideology group. There is no overlap in the topics discussed between liberals and conservatives. Moderates have only one topic in common with either side. Moreover, large differences exist in the proportion of tweets related to topics one group considers important but others do not. For example, the most discussed cluster of tweets for liberals referred to the impeachment of Donald Trump, accounting for about 1% of liberal tweets compared to fewer than 0.1% of conservative tweets, an order of magnitude less. While

Table 2: Five most frequently discussed clusters of tweets by ideology group.

Liberals	**Moderates**	**Conservatives**
Trump impeachment	Trump impeachment	US biolabs
Ukrainian racism	Russian military movements	Ukraine corruption
Refusal to mask	Evacuation of civilians	Ukraine prosecutor firing
UK visa policy	Ukraine coup	Ukraine coup
Ukraine connection	Ukrainian racism	Criticism of Obama Ukraine policy

it was also the most discussed cluster of tweets for moderates, approximately 0.4% of all their tweets referred to the Trump impeachment, a substantially larger proportion than that of liberals yet a substantially smaller than that of conservatives.

For a broader view, we have included in the Appendix Fig.A1, which plots the distributions of the 50 most frequently discussed clusters of tweets according to the user's ideological leaning. Each row represents a different cluster with a label hand-coded by the researcher after examining the ten most relevant tweets in each cluster. The figure suggests that the general distribution of the conversation topics differs among conservative and liberal tweets. Although these clusters do not represent the entire universe of tweets in our analysis, they offers an illustrative snapshot of the differences between conservatives and liberals.

In addition to plotting the general distribution of frequent clusters, we conduct a formal test to determine if these distributions are statistically different from each other (H1). We test the hypothesis with a Chi-squared test, which shows that these clusters of tweets are likely to come from substantively and statistically distinct distributions ($\chi^2_{6,171} = 215,902, p < 0.001$). This finding is consistent with H1, which posits that conservative and liberal users generally post about different topics related to the war in Ukraine.

H2 expects different topics of discussion between moderates and conservatives (H2a) and between moderates and liberals (H2b). A set of two Chi-Squared tests, each of which compares a pair of distributions between conservatives and moderates, and between liberals and moderates, shows that clusters of moderate tweets likely come from substantively and statistically distinct distributions compared to conservative Tweets ($\chi^2_{6,171} = 67,852, p < 0.001$) and liberal Tweets ($\chi^2_{6,171} = 60,213, p < 0.001$). These results support our hypotheses that moderates hold different conversations than conservatives (H2a) and liberals (H2b).

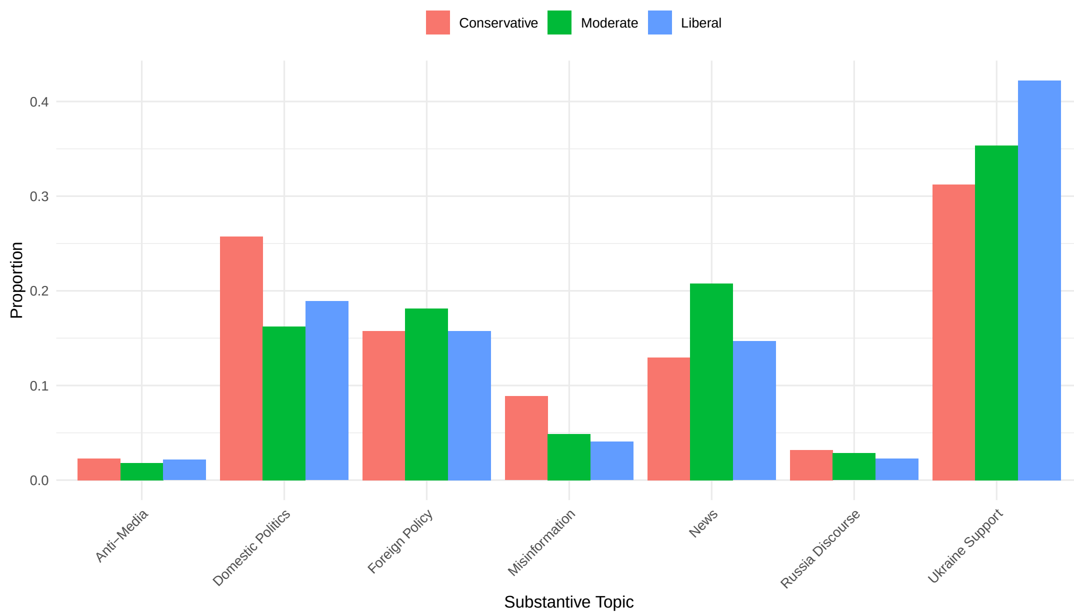
Our results also echo the findings in recent research on moderates that emphasize the true centrist nature of American moderates (*33*). Fig. 1 illustrates how moderates tend to fall in between liberals and conservatives in terms of the frequency with which certain topics are discussed. This gives us observational evidence of moderates' centrist tendencies.

Next, we assess whether conservatives are more likely than liberals to discuss topics related to misinformation (H3). Appendix Fig. A1 offers some suggestive evidence that supports this hypothesis. The most frequent clusters of tweets among conservative users related to conspiracy theories or misinformation, including discussions of "US biolabs" and anti-Semitic conspiracy theories that are used to justify Russia's invasion.

To further test this hypothesis, we identify seven substantive topics related to the discussion surrounding the war in Ukraine and assign each cluster of tweets to one of them (we include the full coding protocol in the Supplemental Information to this paper). Fig. 1 visualizes the proportion of substantive topics discussed by three different ideology groups. Each color represents a different group (Conservative, Moderate, Liberal), while each set of three bars visualizes a substantive topic ("Ukraine Support," "Misinformation," etc.). The height of each bar reflects the magnitude of the proportion of each ideology's tweets devoted to a given topic.

An examination of the proportion of tweets spreading some form of misinformation provides strong evidence in line with H3. As Fig. 1 shows, we categorize the percentage of misinfor-

Figure 1: Proportion of Substantive Topics Discussed by Ideology Groups



mation tweets posted by conservative users (8.9%) as more than twice that of liberal users (4.1%). The results of a formal t-test comparing these two proportions confirm that the difference is statistically and substantively significant.

Our final hypothesis (H4) predicts that liberals are likelier than conservatives to tweet in support of Ukraine. Using the clusters produced by our NLP model, we categorize all tweets that are broadly supportive of Ukraine as Ukraine Support. These include clusters of tweets related to prayers for Ukraine or those lauding the bravery of Ukrainians.

Although support for Ukraine was the most frequently discussed topic in general (see Fig. 1), we find substantive and significant differences among the groups of users separated by their ideological leaning. We categorize 31.2% of all conservative tweets as supportive of Ukraine, compared to 42.2% of all liberal tweets and 35.3% of all moderate tweets.

Discussion

Our findings constitute important evidence that American public discourse about foreign policy on Twitter is divided along ideological dimensions. We document statistically and substantively different engagement patterns in political discussions between conservative and liberal social networks (H1). We also find that moderates discuss topics in ways distinct from those of conservatives (H2a) and liberals (H2b). An in-depth analysis reveals that nearly twice as large of a proportion of conservative tweets compared to liberal tweets contained some form of misinformation (H3). Our results further suggest that a greater proportion of discussion within liberal social media networks than conservative social media networks is devoted to supporting Ukraine, its people, or its leaders (H4). Tweets from moderates lie between the ideological poles for both misinformation and support for Ukraine.

Although our study documents clear domestic ideological divides on a salient foreign policy issue, it comes with four caveats. First, as with any study using social media data, our sample may not be representative of the general public. Given that we only examine those who follow certain media accounts to receive updates on political news, our sample may be more politically engaged and ideologically extreme than an average social media user. Second, we operationalize ideology using an individual user's network. Prior research finds that social media users tend to follow and interact with others who mirror their ideological preferences and lends support for our measurement strategy (*39*). However, our strategy is not immune to the possibility of failing to capture the latent ideological content of a user or their tweets. Third, our process of aggregating tweets into substantive topics through human labeling and supervised machine learning necessarily introduces some degree of imprecision and human error. Though we mitigate this concern by using an NLP model to classify the initial set of

Twitter data into clusters, we cannot fully resolve this issue. For instance, as we discuss in the SI, our model performed well in categorizing support for Ukraine but less well in categorizing support for Russia. Finally, our evidence should be interpreted as descriptive rather than causal in nature. While the patterns we document may align with the empirical implications of causal processes, they are not intended to establish causality.

Our findings also suggest a number of directions for future research. Our study documents the existence of ideological differences on a series of dimensions related to a salient foreign policy issue, including public support for a US ally. However, our design does not allow us to ascertain *why* support varies. Future work could disentangle these mechanisms in greater detail. At least three potential mechanisms are worth exploring. First, the difference in support may come from underlying policy preferences. Conservatives tend to be more sympathetic to military intervention and less supportive of economic aid than liberals (*12*). The Biden administration's emphasis on economic rather than military tools of statecraft may thus explain the difference in support for Ukraine. Second, conservatives might profess less support for Ukraine due to their preexisting dissatisfaction with the incumbent Biden administration. Partisanship may be an underlying factor that leads conservative Republicans to associate praise for Ukraine with the Biden administration and thus refrain from showing support for Ukraine. Indeed, we found that conservatives were more likely than liberals to connect the war in Ukraine to domestic politics, which accords with recent work on partisan types in foreign policy (*16,18,40*). Third, it is plausible that support for Russia among conservatives is related to the spread of misinformation within those same networks, a mechanism largely consistent with existing research on the spread of misinformation within conservative social media networks. Although we find that conservatives are likelier than liberals and moderates to spread misinformation and support Russia, we do not formally test the connection between the two.

Another avenue for future research is whether individuals' political engagement level moderates how they respond to foreign policy issues. Scholars have suggested that there are informational asymmetries between leaders and publics in the foreign policy domain, giving leaders an advantage to frame foreign policy as they desire (*41–43*). Given that many people do not pay attention to politics (*44*) and do not have clear political preferences (*45*), it would be worthwhile to study whether the reactions we identify come from people's true political preferences, or whether they are merely following cues from political leaders such as Donald Trump, who was quick to praise Russian President Vladimir Putin despite Congress's bipartisan support for Ukraine. Such research could provide insight into the potentially heterogeneous effect of elite cues in public opinion (*46, 47*). A related possibility is that Democratic party messages about Ukraine caused a partisan "backlash" among conservatives but not liberals (*47, 48*), though some studies suggest such responses are rare (*49*).

To our knowledge, our findings offer the most direct evidence yet that political discourse on social media platforms on foreign policy issues in the United States is different for conservatives, moderates, and liberals. These results suggest that the contested nature of American domestic politics also extends to salient foreign policy issues.

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Competing Interests

The authors declare no competing interests.

Data Availability Statement

The datasets generated during and/or analyzed during the current study will be made available upon publication in an OSF repository.

Ethical Approval and Informed Consent

This article does not contain any studies with human participants performed by any of the authors.