Wording Matters: the Effect of Linguistic Characteristics and Political Ideology on Resharing of COVID-19 Vaccine Tweets

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Social media platforms are frequently used to share information and opinions around vaccinations. The more often a message is reshared, the wider the reach of the message and potential influence it may have on shaping people's opinions to get vaccinated or not. We used a negative binomial regression to investigate whether a message's linguistic characteristics (degree of concreteness, emotional arousal, and sentiment) and user characteristics (political ideology and number of followers) may influence users' decisions to reshare tweets related to the COVID-19 vaccine. We analyzed US English-language tweets related to the COVID-19 vaccine between May 2020 and October 2021 (N = 236,054).

Tweets with positive and high-arousal words were more often retweeted than negative, low-arousal tweets. Tweets with abstract words were more often retweeted than tweets with concrete words. In addition, while Liberal users were more likely to have tweets with a positive sentiment reshared, Conservative users were more likely to have tweets with a negative sentiment reshared. Our results can inform public health messaging on how to best phrase vaccine information to impact engagement and information resharing, and potentially persuade a wider set of people to get vaccinated.

CCS Concepts: • **Human-Centered Computing → Collaborative and social computing**; **Human-Computer Interaction (HCI)**; • **Applied computing** → *Law, social & behavioral Sciences.*

Additional Key Words and Phrases: COVID-19, vaccination, sentiment, emotional arousal, concreteness, political ideology, social media, resharing, information retransmission, message diffusion, information dissemination, negative binomial, linguistic style

1 INTRODUCTION

The global outbreak of COVID-19 has made it crucial for public health and government agencies to inform the public in a timely manner and provide guidance on vaccinations, to prevent the further spread of the virus and mitigate effects for those infected. Social media platforms such as Twitter are frequently used to share information and express public opinions around vaccinations, and can be a useful tool to disseminate important vaccine information [2]. However, government agencies have experienced difficulties in effectively reaching members of the public [1]. Given the vast amount of information being posted online, information that is reshared increases its exposure and thus expands the reach of a message. In turn, exposure to information about vaccines can impact the potential influence it may have on people getting vaccinated or not. For example, studies have found that vaccine hesitancy is strongly influenced by the amount of anti-vaccination information people consume on social media [9, 51, 100]. It is therefore important to understand what factors may influence the resharing of messages

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in the context of the COVID-19 vaccine. Further, message characteristics, such as its structure, content, and style, can affect the rate at which messages are shared [83] and how persuasive information can be [88].

In this paper, we investigate whether we can predict the number of times tweets related to the COVID-19 vaccine get retweeted based on their linguistic characteristics (the degree of concreteness, emotional arousal, sentiment), as well as user characteristics (the user's political ideology, number of followers). We focus on Twitter as it has frequently been used as a platform to discuss information related to vaccinations [2], and has been found to be an influential platform in public decision-making around vaccinations [45]. We consider a user's political ideology as it has been shown to play a key factor in people's vaccine attitudes [66]. Therefore, a message may get reshared more frequently if it aligns with someone's political views.

Previous HCI research has studied the effects of social media communication in a number of contexts, such as war [22], natural disasters [80, 97], mental health [21], smoking cessation [56], and same-sex marriage discussions [55]. These studies highlighted how communities leverage social media for communication and discussion, and how social media platforms can play a major role in disseminating information and amplifying certain information over others. We contribute to this area of research by focusing on social media communication regarding the COVID-19 vaccine. It is important for HCI research to understand the role of social media in COVID-19 vaccine communication and how information on social media can be best phrased to impact engagement and information resharing, so that it reaches a wider audience and potentially persuades a wider set of people to get vaccinated.

2 BACKGROUND

2.1 Factors that influence online message engagement and resharing

Effective public health communication plays an important role during a pandemic in informing the public about virus transmission and prevention [96]. For this purpose, social media can be a useful platform to directly reach people in a timely manner. Social media not only allows users to engage directly with information, for example through comments or interactive links, but also enables users to amplify messages through resharing.

Resharing, that is, passing messages from one account to another or retweeting a message, is crucial in amplifying messages on social media [86] and potentially influencing more people. Previous work on social media has identified a number of factors that affect both engagement with, as well as passing on, that information. Research focusing on online engagement of government agencies, such as the National Weather Service [78], found that the use of hashtags, URLs, and direct replies to messages of other users, facilitated people's interaction and engagement with messages on Twitter [61]. However, other studies found that the inclusion of URLs and direct replies reduced message sharing [83, 102]. A potential explanation given by the authors is that people may click on a link and get distracted by the external source, and forget to come back to Twitter to retweet the original tweet.

Vos et al. [98] studied tweets during various threat situations (such as a weather emergency or a disease outbreak) and identified a number of factors that influence message resharing in these types of situations: the time at which a message is sent, account characteristics (e.g., whether the message came from a verified organization, the number of followers associated with an account), and the design of a message (e.g., its contents and structural features, whether the message contained media such as images and videos). In addition, multiple studies found that if a message contains information about the severity of the threat and includes actionable and practical information, it is more likely to be reshared [8, 83, 84, 86, 102]. In contrast, warning messages about an impending threat that do not include any instruction on what action to take are less likely to be reshared [83]. Health-related tweets are also more likely to be reshared if they come from a reputable health source [102]. Lastly, Tan et al. [87] found a positive correlation between message length and number of retweets (i.e., the number of times a tweet was retweeted), but only if a longer message was informative, i.e., containing more useful information than shorter messages.

2.2 The role of emotion and linguistic features on message resharing

It is not only the type of information (such as actionable information and inclusion of images) that can affect message resharing: an important component is the emotion and linguistic style in which that information is presented. Emotionally charged language can grab people's attention [14, 82], improve retention of the message content [44], and motivate people to reshare its content with others [57]. In this paper, we focus on the linguistic features sentiment, arousal, dominance and concreteness. Our choice of measures is informed by Osgood's [62] dimensional theory of emotion, which measures emotions along three dimensions: sentiment, arousal and dominance. Our decision to include concreteness is informed by construal-level theory, which posits that people put more weight on high-construal (abstract) messaging in risk perception and decision-making. Concreteness of vaccine tweets may therefore play an important role in online vaccine discussions, and affect perceived risk of COVID-19 vaccines and the decision to get vaccinated. We next discuss relevant work that has explored how the four linguistic features of sentiment, arousal, dominance and concreteness affect online engagement, resharing, and persuasion.

Studies focusing on sentiment have found differing results for its effect on resharing and engagement. In general, information expressing a negative sentiment elicits more reactions: Facebook postings with a negative sentiment receive more comments [81], and a study looking at vaccine tweets found that those with negative sentiment toward vaccines attracted higher engagement [33]. This may be explained by the 'negativity bias' [7], indicating that people give a higher weight to negative events and news.

However, studies focusing on resharing of messages found that including either positive or negative sentiment (rather than neutral words) can both increase message resharing [8, 30, 92], and whether positive or negative messages are reshared more may depend on the specific context and message topic.

For instance, work that studied Spanish political tweets during a national referendum [39] and news tweets from CNN [77] found that negative sentiment increased the likelihood of tweets being reshared. On the other hand, with US-based health-related tweets (i.e., sharing information around cardiovascular disease), more retweets were found with tweets showing a sense of support to others through positive and encouraging messages [102].

To control for message content, Tan et al. [87] compared tweet pairs containing similar information and found that the tweet that contained more positive words out of the pair was retweeted more. The effect of sentiment on retweets may also have a temporal component: when considering the trend of message resharing over a one-month time period, tweets with a negative sentiment may have a faster initial spread, but tweets with a positive sentiment achieve a higher number of retweets overall [25].

In addition to sentiment, the emotional arousal (i.e., the emotional intensity) of a tweet can influence people's responses. Police messaging tweets with high levels of emotional arousal increased engagement (through likes and comments) and resharing [49]. Arousal can have a particularly strong effect when combined with negative sentiment: news-related tweets from CNN were retweeted more often if they contained high-arousal words, but only if the tweet had a negative sentiment [77]. Additionally, past work on politics in the media found that uncivil or rude speech may intensify negative reactions, but also increases recall of the content and motivates people to reshare the content with others [57], thereby widening its spread.

Lastly, when looking at tweets during an acute event, such as a natural disaster, neither positive nor negative sentiment had an effect on resharing: instead, when the use of concrete language played a more important role as it reduced uncertainty around the current situation [48]. People may perceive acute emergency events as an immediate threat and need concrete information to act on it. People process concrete words more quickly than abstract words [63], which may impact their decision to reshare information during a crisis such as a natural disaster. When considering vaccine tweets during the COVID-19 pandemic, tweets with concrete words were only more likely to be retweeted if they contained antivaccine hashtags [76]. Studies looking at the role of concreteness in offline discussions found that the use of concrete words was also more persuasive [46] and that people rely more on concrete information to make decisions [65].

The role of concreteness can be further understood through construal level theory (CLT), a theory used to understand concreteness in risk perception and decision-making [91]. The theory postulates that people think about psychologically distant realities with an abstract mindset (high construal), and psychologically proximal realities with a more concrete and detailed mindset (low construal). So while people may rely more on concrete information in situations of imminent threat, such as seeking shelter from a natural disaster, the same may not apply for situations that seem more distant, such as getting vaccinated to protect against the possibility of contracting COVID-19. Indeed, research applying this theory to decision-making found that people put more importance on high construal messaging when making long-term decisions [79], and vaccine messages using more high construal messaging led to higher intention to vaccinate [42]. We contribute to this line of work by studying whether the effect of high construal, abstract messages on vaccination is also reflected in online behavior on social media in the form of resharing vaccine messages.

2.3 The role of linguistic features on persuasion in online discussions

Linguistic factors such as sentiment and arousal not only play a role in resharing, but can also affect the persuasiveness of online messages [88]. For example, basic characteristics of the argument itself, such as valence, framing, and intensity [3, 34] can considerably influence how persuasive an argument is.

Tan et al. [88] studied online discussions on ChangeMyView, an active Reddit community where users can provide their opinion on various topics, inviting other users to contest this opinion, and confirm when these discussions have changed their view. While the authors did not find any effect of concreteness on the persuasiveness of online messages, they instead found that it was more persuasive to use calm (low-arousal) language; a tone that was too intense (high-arousal) decreased persuasion. Furthermore, persuasive opening arguments used less positive (low-valence) words, though valence often rose over the course of an argument. Other message features that were indicative were length (persuasive messages tend to be longer), and similarity with the original argument (persuasive messages are more dissimilar in terms of words that are used). Given its role in influencing the persuasiveness of information, we study whether language factors can impact the likelihood of people resharing information in the COVID-19 vaccine debate.

2.4 The role of political ideology

Prior studies have explored how the sentiment, arousal and concreteness of a message can affect both message resharing and persuasian on social media. However, few studies have looked at how someone's political ideology moderates the relationships between linguistic characteristics and resharing. Political ideology may be an important factor to consider as it is known to play a role in people's stance on the COVID-19 vaccine. US-based studies have consistently found that people who identified as conservative were significantly less likely to report their intention to be vaccinated [41, 47, 66]. People may therefore be more likely to reshare information that aligns with their sentiment and political views: for example, conservative users may get more retweets if a vaccine tweet is negative (and aligns with their audience's overall sentiment) than when a tweet has a positive sentiment. In addition, wording and language in itself can be informed by individual characteristics (i.e., the theoretical framework lexical hypothesis proposes that individual characteristics such as personality can influence language [27]); for instance, an individual's personality traits can predict their language use both on social media [64] and in offline communication [95]. Political ideology has also been found to be related to language. For instance, the linguistic characteristics of different languages (such as English and Spanish) can predict and sway the political opinion of its speakers [68, 69], and someone's political ideology can influence their choice of words [13]. This raises the question of whether certain styles, such as concrete or high-arousal words, are used more or less, and whether they resonate differently with different audiences.

2.5 Communication science to inform public health messaging

The COVID-19 pandemic has presented the public with an overload of misinformation about COVID-19 and vaccines, which can lead to cognitive fatigue [37]. In addition, social media facilitates a fragmented information environment where many pieces of information compete for people's attention [24, 75]. It is therefore crucial for public health to understand what messaging strategies can capture people's attention online, and what will motivate them to comply with public health guidelines [37]. While the effect of arousal, sentiment and concreteness on resharing has been explored in contexts such as natural disaster events [48], political elections [39], and social movements [22], it has not been explored in online discussions of COVID-19 vaccines to help shape communication strategies. A recent literature review demonstrated the promise of using communication science to inform public health messaging during the COVID-19 pandemic [101]. In this paper, we therefore focus on the effect of arousal, sentiment and concreteness on resharing of COVID-19 vaccines, to inform public health messaging.

In addition, misinformation and negative sentiment around vaccinations exist on both sides of the political spectrum [18, 19], making it important to not only understand communication implications for public health messaging in general, but also whether it differs depending on ideology. The communication implications to encourage people to get vaccinated may be different for the sides, as Liberals and Conservatives rely on different moral values to motivate their vaccine stance [13].

2.6 Research Questions and Contributions

In summary, while previous work has identified factors that can influence online message resharing, such as linguistic factors, and has highlighted differences in political ideologies in terms of their sentiment toward the COVID-19 vaccine, little research has examined these two factors in conjunction. We feel it is important to investigate how political ideology may moderate the effect of linguistic factors on message resharing related to the COVID-19 vaccine, especially on Twitter, since it is such a broad public platform. In this paper, we investigate whether we can predict retweet count based on linguistic characteristics of a tweet (concreteness, emotional arousal, sentiment) and how the political ideology of a user might modify this, controlling for number of followers. We address the following research questions:

- RQ1: Is there a relation between political ideology and linguistic characteristics of a message?
- RQ2: How do linguistic characteristics affect resharing of messages concerning the COVID-19 vaccine?
- RQ3: Does political ideology moderate the effect of linguistic characteristics on message resharing?
- RQ4: Does the number of followers of a tweet affect resharing of messages concerning the COVID-19 vaccine?

3 METHOD

3.1 Data collection

To identify tweets related to the COVID-19 vaccine, we utilized the Twitter COVID-19 Stream [93]. The stream filtered tweets using a list of COVID-19-related terms defined by Twitter (for a complete list of terms, see [93]). We focused on Twitter as it has been frequently used as a platform for public discourse around vaccinations [2, 29]. As such, Twitter can be a useful source to explore discussions and sentiment related to the COVID-19 vaccine.

The initial dataset of 3.4 billion tweets were collected from May 15, 2020 to October 31, 2021, which consisted of the original tweets as well as the retweets. Filtering was first done to limit tweets originating within the US and then to eliminate duplicate tweets and retweets. This created a dataset of 539,652 tweets. Since our research addresses political ideology, we then only included users for whom we were able to estimate their political ideology, resulting in a dataset of 236,054 tweets.

3.2 Geo-filtering and geo-tagging

The collected filtered stream dataset contains geo-tags provided by Twitter. The primary geo-filtering was conducted with those geo-tags and only including tweets with "US" as the "country code" field. Since only the original tweets have geo-tags from Twitter, we also filtered out duplicated tweets and retweets in this step.

A large portion of the provided geo-tags only include rough location names, such as state names or city names, which are not as accurate as coordinates. A further geo-tagging process was applied to convert all location names to approximated coordinates.

3.3 Data pre-processing

Words were converted to lowercase, and the Python package gensim [106] was used to remove white space, URLs, emoticons, symbols, and punctuations. The Stanford Core NLP [70] Python package was used to tokenize each tweet into words, and the Python package NLTK [11] was used to lemmatize words, and remove standard English stopwords found in the NLTK's English stop word database, such as "I" and "the".

3.4 Measures

Our measures address both core linguistic features and political ideology (discussed below). To measure core linguistic features we relied on three core word-level features based on Brysbaert et al. [15] and Warriner et al. [99], namely concreteness, arousal, and sentiment. We considered the full text of the tweet to measure its linguistic features: if a user retweeted something and provided an additional comment, both the comment and the text of the original tweet were taken into account. If the retweet did not have a comment, the text of the original tweet was included. The total concreteness, arousal, and sentiment scores of a tweet were calculated by taking the mean score of individual word scores and only considered words that were found in the linguistic databases (and not out-of-vocabulary words), so the total score was not sensitive to message length.

3.4.1 Concreteness. Concreteness measures the degree to which the concept denoted by a word refers to a perceptible entity. Examples of abstract words are spirituality and essential, and examples of concrete words are vaccine and person. We used Brysbaert et al.'s [15] database to assess concreteness. This database contains 40,000 English lemma words that have been given concreteness ratings by 4,237 native English-speaking Amazon Mechanical Turkers; on average 25 raters were used for each word. The ratings come from a larger list of 63,000 words and represent all English words known to 85% of the raters. Words were rated on a scale of 0 to 5, where 0 is the least concrete and 5 is the most concrete. Utilizing this database, we used the R package doc2concrete [103] to calculate the concreteness of tweets.

3.4.2 Arousal. Arousal measures the intensity of emotion expressed in text. Examples of calm, low-arousal words are "dull" and "library", and examples of high-arousal words are "infuriated" and "exciting". In addition to arousal, we measured the linguistic features that capture a word's dominance and valence but as these measures were correlated with each other and the measure for sentiment, these were not included in our final models. Dominance measures the degree of control expressed by a word. Low-dominance words often indicate weakness (e.g., sickness), while high-dominance words evoke success and power (e.g., completion, profit). Valence measures how pleasant the word's denotation is. Examples of low-valence words are "cancer" and "murder," while examples of high-valence words are "love" and "sunshine."

The Affective Norms for English Words (ANEW) database was used to measure arousal, dominance, and valence [99]. ANEW is a database of around 14,000 English lemma words that have been manually rated by human volunteers on arousal, dominance, and valence. Words are rated on a scale from 1 to 9, where 1 is the least arousing/dominant/valent, and 9 is the most arousing/dominant/valent. The scorers for the ANEW database were 1,827 US residents recruited from Amazon Mechanical Turk. Each person rated approximately 350 words and each word was rated between 18 and 30 times. Utilizing this database, we adapted Zhou's [105] Python script to calculate dominance, arousal, and valence ratings for each tweet.

For each word in a tweet, we searched for the word in the database and stored its individual arousal, dominance, and valence values. We calculated overall arousal, dominance, and valence ratings for a tweet by taking the mean of the values for each word in that tweet.

3.4.3 Sentiment. Sentiment determines whether a word is negative, positive, or neutral. Examples of negative words are "bad" and "frustrated," and examples of positive words are "happy" and "beautiful." The R package *sentimentr* [72] was used to calculate the sentiment of tweets. Negative scores on this continuous measure reflected a negative sentiment and positive scores reflected a positive sentiment; a score of 0 reflected a neutral sentiment. Sentimentr uses the Jockers-Rinker lexicon [40], which contains 11,709 words scored by Amazon Mechanical Turkers. The package combines scores from the lexicon with a group of 140 valence shifters, which can take a value of 1 to 4 [58]. Valence shifters are words that alter or intensify the meaning of the polarized words. For example, the word 'not' before 'happy' would switch the polarity of the word 'happy' from positive to negative. Sentimentr considers 5 words before a polarized word, and 2 words after the polarized word as potential valence shifters.

3.4.4 Political ideology. Someone's political ideology broadly encapsulates their set of values, ideas, and principles of how society should work. In this paper, we considered the political ideology of Twitter users, and adopted Barbera et al's validated methodology [4] to estimate their political ideology. The estimation is based on the assumption that the more liberal or conservative accounts a user follows, the more likely that user identifies with the same ideology. The algorithm was validated in prior work by estimating the ideology of known democrats on Twitter such as Barack Obama and known conservatives such as George Bush [5]. We further tested its validity by randomly sampling six Twitter users from our dataset. Three members of our research team independently coded the political ideology of each user. Intra-class coefficient (ICC) [26] was used to assess inter-coder reliability between the three human coders and Barbera et al's model. ICC estimates and their 95% confident intervals were calculated using the R irr package [28] based on a mean-rating (k = 4), absolute-agreement, two-way random effects model. The ICC among the three human coders was 0.91 (0.435-0.986) and the ICC between the three human coders and the model was 0.93 (0.711-0.989), indicating good to excellent reliability (see [43]) and further validating the algorithm. We used the Python package tweepy [73] to scrape the Twitter accounts that each user follows, and the R library tweetscores to estimate a user's ideology score [4].

Tweets can originate from a verified organization or account, or from an individual user. The tweetscores package included pre-estimated ideologies for well-known political accounts and media outlets (e.g., CNN or Fox News). These known ideology scores were then used to estimate individual Twitter users' ideologies. A user's ideology score was calculated based on the accounts they followed. We used political ideology as a continuous variable, and users either had a score below zero (which was associated with liberal views) or a score above zero (which was associated with conservative views). There were no cut-off points for the ideology scores, and the more negative or positive a score, the more liberal or conservative the user. In the analyses, we only included users and tweets for which an ideology score could be calculated. A user who was not following any accounts present in the database used by the algorithm could not be assigned a political ideology score.

Table 1. Correlation matrix of model variables showing a moderate to strong correlation between dominance and valence/sentiment scores. Dominance and valence were removed from the final model.

	Ideology Score	Concreteness	Arousal	Dominance	Valence	Sentiment Score
	1					
Concreteness	-0.01	1				
Arousal	0.06	0.02	1			
Dominance	-0.05	-0.05	-0.34	1		
Valence	-0.05	0.01	-0.12	0.72	1	
Sentiment Score	-0.02	-0.02	-0.13	0.42	0.48	1

3.4.5 Political Ideology Variable Transformed for Moderator Variable Analysis. While we use political ideology as a continuous variable in our models, for the purpose of plotting the data, Figure 4 (which visualizes the interaction effects between political ideology and arousal/sentiment) shows ideology divided into three political ideology categories to aid the interpretability of the figure and understand the direction of the effects. We plotted the data divided into three ideology groups: Liberals (with ideology scores -1 or lower, N = 95,367), Moderates (scores between -1 and 1, N = 86,088), and Conservatives (scores 1 or higher, N = 54,599). These score cut-offs were based on previous studies for political groupings based on ideology score [4].

3.5 Correlations Among Variables

Before the model was tested, the predictor variables were assessed for correlation. The correlation matrix of the variables is displayed in Table 1. Upon initial inspection of the variables, we found that dominance was strongly correlated with valence (the correlation value exceeded 0.70, see [16] for more information), and was removed from the model. Furthermore, because valence and sentiment measure similar linguistic characteristics and were moderately correlated, we decided to only include sentiment and remove valence from our model. The correlation matrix showed no strong correlations among the other variables.

3.6 Data Analysis

First, to investigate a potential relationship between a user's political ideology and their tweets' linguistic characteristics (concreteness, arousal, and sentiment), we used LMER [6] in R to run a linear mixed-effects model for each characteristic, using ideology as the independent variable. A user's unique Twitter ID was included as a random effect to control for tweeting frequency.

Second, we used a negative binomial regression to investigate how linguistic characteristics affect the number of retweets, and whether political ideology moderates the effect of linguistic characteristics on the number of retweets. The retweet data was overdispersed (the dispersion parameter was significantly greater than 0 at 0.067), and should thus be estimated using a negative binomial model rather than a Poisson model to account for the highly skewed distribution of retweet count and excessive zero values (i.e., tweets that were not retweeted) [32]. The model was fit using the R packages MASS and pscl [104]. The dependent variable of the model was the number of retweets, i.e., the number of times a tweet was retweeted. The predictors were the concreteness, arousal, and sentiment scores of a tweet, and the estimated political ideology of a user. Political ideology was also tested as a moderating variable. A user's number of followers was added as a control variable, as tweets that come from users with a large number of followers are likely to get retweeted more [85]. Figure 1 shows our proposed model.

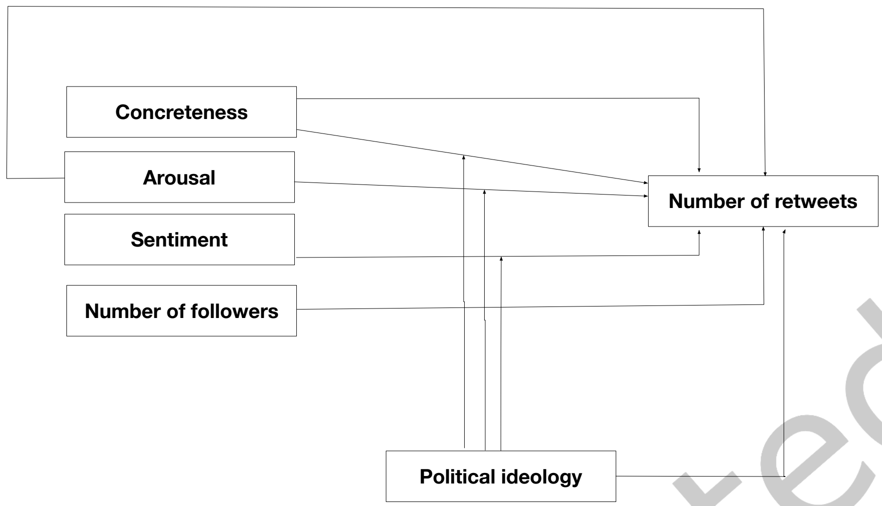


Fig. 1. The proposed model investigating the effect of concreteness, arousal, and sentiment on number of retweets, with political ideology as a moderating variable and number of followers as a control variable.

Table 2. Summary of model variables.

	Mean (SD)	Min	Max
Number of retweets	3.0 (136.0)	0	32,234
Concreteness (0-5)	2.38 (0.40)	0	5
Arousal (0-9)	4.45 (0.54)	1.95	8.05
Sentiment	0.02 (0.20)	-2.21	1.69
Ideology score	-0.28 (1.32)	-2.47	2.47
Number of followers	5,003.19 (26,770.53)	0	910,869

4 RESULTS

Figure 2 shows the retweet count distribution. The distribution was positively skewed with a long tail (min = 0, max = 32,234, skewness = 151.468, kurtosis = 28,234.34). 43,513 tweets (18%) were retweeted, with a mean retweet of 3.0 (SD = 136.0, median = 0). Table 2 shows a summary of the other model variables.

4.1 The relation between political ideology and linguistic characteristics of tweets (RQ1)

Our first research question asked whether there is any relationship between a user's political ideology and their messages' linguistic characteristics. Conservatives expressed more negative sentiment and higher arousal than Liberals, and there was no significant difference between ideologies in terms of a message's concreteness. Figure 3 plots ideology against the three linguistic characteristics (concreteness, arousal, sentiment), and shows that very Conservative users (i.e., ideology scores > 1) more often used high-arousal words (3b). In addition, sentiment scores had a trend of becoming more negative among extreme ideology score users compared to moderate ideology score users (3c). However, very Liberal ideology score users (i.e., ideology scores < -1) still showed a slightly positive sentiment, whereas very Conservative users (i.e., ideology scores > 1) showed a negative sentiment. Lastly, Figure 3a shows that more concrete words were used by more extreme ideologies (both very

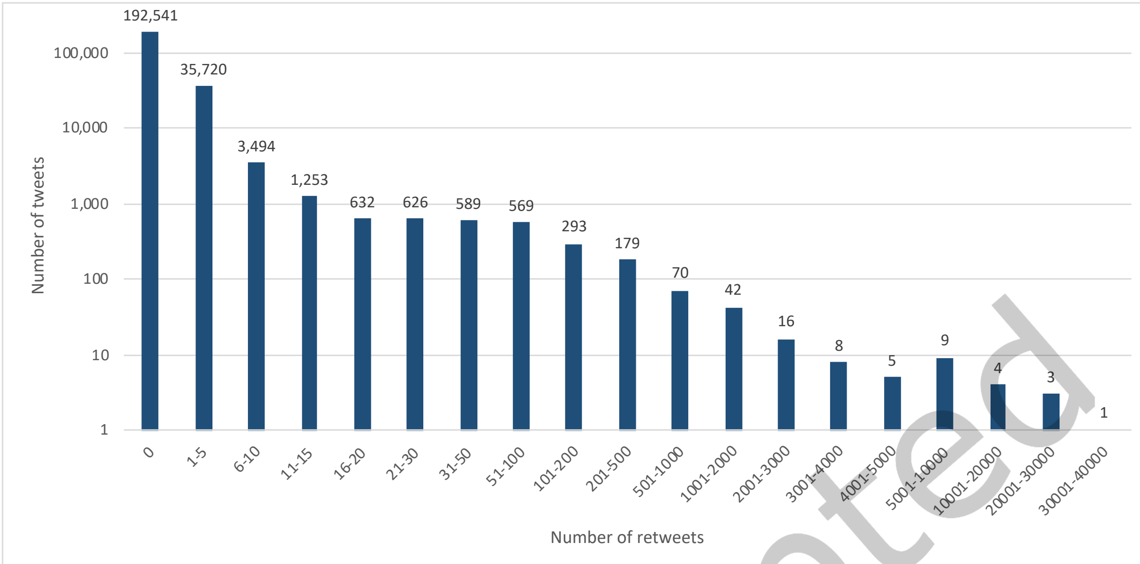


Fig. 2. The majority of tweets (N = 192,541, 82%) had zero retweets. However, a small fraction of tweets were retweeted over 1,000 times. It is of note that in order to scale and fit the plot, bin sizes are of unequal size.

Table 3. Linear mixed-effects model results for the effect of political ideology on concreteness.

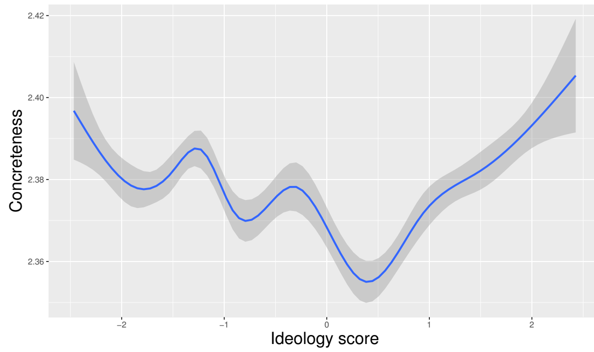
	Estimate	Std. Error	T value
(Intercept)	2.3811	0.0015	1,607.4
Ideology Score	-0.0013	0.0011	-1.2
AIC		221,932.2	

Liberal and very Conservative) compared to moderate ideology scores. To understand whether these trends were significant, we ran separate linear mixed-effects models for each linguistic characteristic, with political ideology as the independent variable. Tables 3-5 summarizes the model results for each feature. The results indicate that arousal and sentiment scores were significantly different by ideology score, and that differences in concreteness scores were insignificant. As the ideology score became more positive (i.e. more conservative), arousal increased and sentiment scores became more negative.

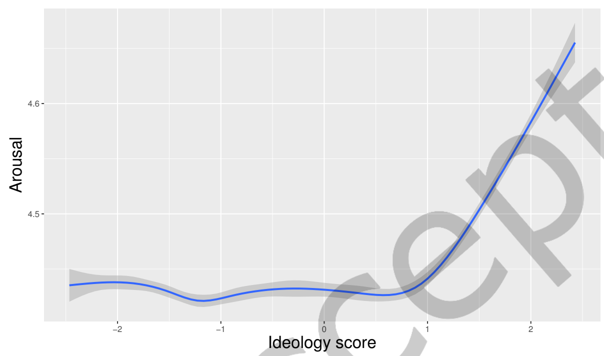
Table 4. Linear mixed-effects model results for the effect of political ideology on arousal.

	Estimate	Std. Error	T value
(Intercept)	4.4506	0.0017	2,547.4
Ideology Score	0.0179	0.0013	13.7 ***
AIC		358,575.7	

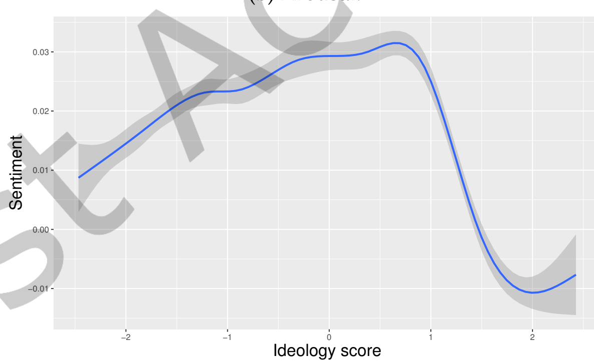
***P < 0.001



(a) Concreteness.



(b) Arousal.



(c) Sentiment.

Fig. 3. Three plots of ideology score and the linguistic features (a) concreteness, (b) arousal, and (c) sentiment. Loess smoothing [36] has been applied to show the overall trend, rather than individual data points, and highlights the relationship between variables.

Table 5. Linear mixed-effects model results for the effect of political ideology on sentiment.

	Estimate	Std. Error	T value
(Intercept)	0.0205	0.0006	33.3
Ideology Score	-0.0030	0.0005	-6.6 ***
AIC		-94,837.5	

***P < 0.001

Table 6. Negative binomial regression model results predicting retweet count.

Predictors	Estimate	Std. Error	Z value
(Intercept)	-0.0406	.0897	-0.453
Concreteness	-.6562	.0230	-28.574 ***
Arousal	.3163	.0160	19.826 ***
Sentiment	.1127	.0431	2.612 **
Ideology Score	1.200	.0657	18.262 ***
Number of followers	.00008	.0000003	245.901 ***
Concreteness * Ideology Score	-.0439	.0172	-2.553
Arousal * Ideology Score	-.2.505	.0116	-21.574 ***
Sentiment * Ideology Score	-.6837	.0318	-21.496 ***

**P < 0.01, ***P < 0.001

4.2 Modeling the effect of linguistic characteristics on message retweets (RQ2), modified by ideology (RQ3), controlled by number of followers (RQ4)

We next address how linguistic characteristics affect message retweets (our second research question), and whether political ideology moderates the effect of linguistic characteristics on message retweets (our third research question). Linguistic characteristics affected message retweets in the following ways: tweets with positive, high-arousal and abstract words were significantly more often retweeted than negative, low-arousal and concrete tweets. Political ideology moderated the effects as follows: Liberal users were significantly more likely to have tweets with a positive sentiment reshared, while Conservative users were significantly more likely to have tweets with a negative sentiment reshared. We discuss these results in more detail below.

Results (summarized in Table 6 indicate that retweeting of COVID-19 vaccine tweets was significantly influenced by concreteness, sentiment, and arousal of the message (RQ2). The more abstract (i.e., less concrete) a message, the more positive sentiment, and the higher the proportion of high-arousal words used, the more likely a message was retweeted.

To answer whether political ideology moderated the influence of these message features on retweeting (RQ3), our results indicated that sentiment and arousal were significantly moderated by political ideology while concreteness was not (RQ3). As shown in Figure 4, the effect of arousal on retweets (i.e., high-arousal tweets receiving more retweets) was stronger among Liberals than Conservatives and Moderates. For the effect of sentiment on retweets, the relationship differed among political ideology. Among Liberal Twitter users, more positive vaccine tweets were retweeted, while among Conservative Twitter users, more negative vaccine tweets were retweeted.

Lastly, a user's number of followers had a significant effect on the number of retweets that a tweet received (RQ4). Users with more followers were likely to receive more retweets.

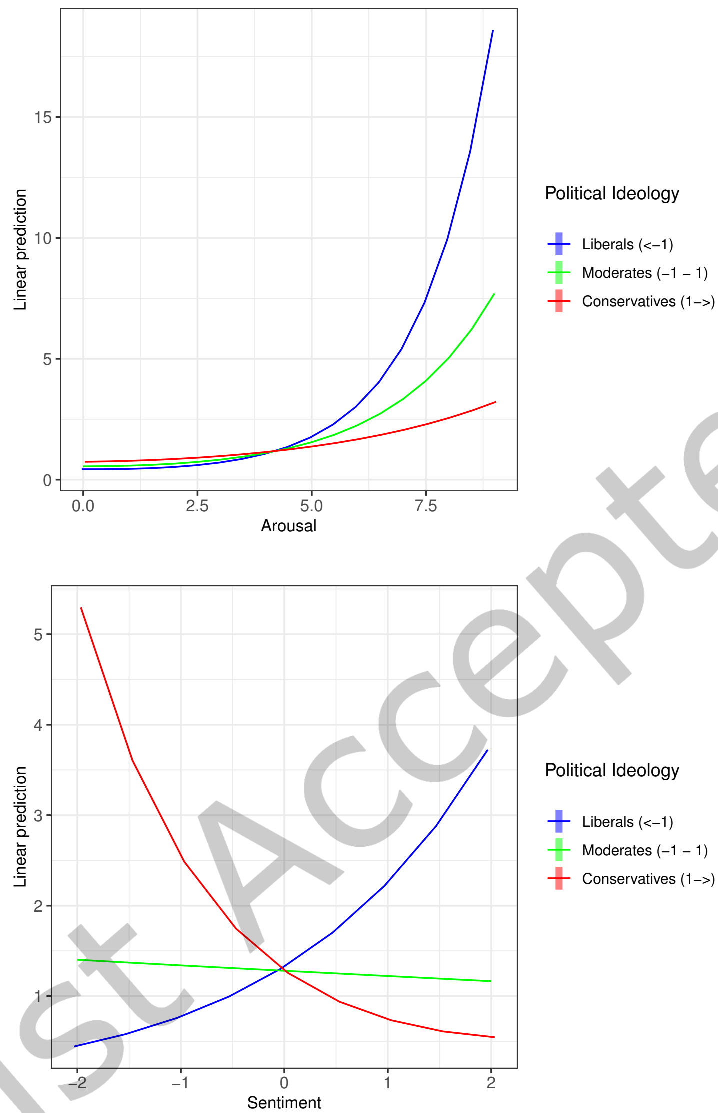


Fig. 4. Figures showing the interaction effects between a Twitter user's political ideology and a tweet's (a) arousal and (b) sentiment.

5 DISCUSSION

This paper investigated whether linguistic characteristics of a tweet (concreteness, emotional arousal, sentiment) and user characteristics (political ideology and number of followers) can predict retweet count. Similar to most tweets as identified in prior work [83, 102], the majority of tweets in our dataset did not get retweeted. For the subset that did get retweeted, we found that the degree of concreteness, arousal, sentiment of a message, as well as a user's political ideology and number of followers, impacted the number of retweets it received.

5.1 Concreteness

Concreteness was negatively associated with number of retweets, indicating that more abstract (i.e., less concrete) messages were more likely to get retweeted. An example of an abstract message in our dataset is *"Really... while America's patriotic first responders have to mask up… vaccinated to provide medical attention to those who refused to mask and get vaccinated. How is this right? Why should first responders deal with the unpatriotic people who refuse to help themselves?"*. While this tweet has some concrete words such as "mask", it also mentions more abstract concepts such as providing medical attention and help. On the other hand, tweets from our dataset with high concreteness scores tended to have short statements composed of concrete words, such as *"Mandate vaccine passports"* and *"Mask, distance, wash"*. The finding that abstract messages were more likely to get retweeted seems to contradict prior work that concrete messages are retweeted more often [48], and the effect of concreteness may depend on the specific situation and context of tweets. Lee et al. [48] found that the use of concrete language played an important role in urgent, highly uncertain events such as a natural disaster, as it can reduce uncertainty around the current situation. Concrete information is processed more quickly than abstract information [63], which may be crucial in urgent crisis situations. In contrast, we considered the online COVID-19 vaccine debate over a time period of 18 months rather than a specific incident. During this time period, there were incidents that were more urgent than others. While a longitudinal analysis is out of scope for this paper, future research can address more specifically if concreteness might be related to certain situations, for example during moments when there were rises in COVID-19 cases.

The inverse effect of concreteness on message resharing may also be related to the audience a message reaches, and whether their values are aligned with the Twitter user tweeting the message. In political speeches, abstract messages are more effective in convincing an audience whose political positions are similar to the speaker's, and concrete messages are more effective in convincing an audience whose political positions differ from the speaker's [52]. When an audience has similar views to the speaker, there is certain common ground that can be taken for granted and people can rely on more abstract, figurative language. As people are more likely to follow accounts whose views align with their own views [4, 76], this may explain why people were more likely to retweet more abstract messages.

5.2 Sentiment

We find that Liberal messages with a positive sentiment were more likely to get retweeted, which is in line with previous work on health-related tweets showing that messages showing themes of hope, support and encouragement gained more retweets [102]. An example of a positive tweet in our dataset is *"Proud to support this important initiative @ChiPublicHealth to improve equity of vaccine distribution in our most affected communities and also h/t to @alikhan28 our chief policy advisor and @halleh13 our director of community outreach who mobilized volunteers! #protectchicago"*. An example of a more negative tweet is *"Toxic ass, nasty ass vaccines!!!! Disgusting!"*.

This finding contrasts with prior research that found tweets expressing negative sentiment towards the vaccine attract more public engagement [33], and further indicates that certain engagement with content, for example, by clicking on links or replying to a message, does not necessarily mean the content will also be reshared [83, 98]. For example, previous studies on health emergencies found that tweets with URLs receive more engagement from users who see the tweet (e.g., clicking on URLs, replying to the message), but that tweets with URLs are less likely to be retweeted and shared with others [83, 98]. People may engage with the tweet by clicking on the URL, but then get distracted by the external source, and forget to come back to Twitter to retweet the original tweet.

5.3 Arousal

In line with other Twitter studies [14, 49, 77], high-arousal messages were more likely to be retweeted, such as the high-arousal message *"Abbott is fully vaccinated. You are a disgusting liar!"* Common characteristics of high-arousal tweets were use of exclamation marks, all-caps and/or curse words. An example of a calmer, low-arousal message in our dataset is *"If you're vaccinated, are you comfortable with this and will you be unmasking? If you're not vaccinated, how does this change make you feel? #COVID19"*

However, while high-arousal words may have increased message resharing, previous work found that low-arousal words were more persuasive in winning an argument on social media discussions [88]. This sheds an interesting light on resharing versus persuasion. First, previous studies on persuasiveness on social media have typically focused on Reddit [88]. Reddit allows for longer messages compared to the 280-character limit on Twitter, which can affect the persuasiveness of linguistic styles [53]. Second, Tan et al. [88] explored a Reddit discussion forum in which people were open to being persuaded and having their opinions changed. Low-arousal words may be more persuasive in an environment where people have time and space to process more information, compared to a platform with limited space to grab one's attention [14]. In addition, on Reddit platforms longer messages were found to be more persuasive [87, 88]; the same may not apply to Twitter.

Resharing messages is one first important step in increasing information exposure on social media. The amount of exposure to anti-vaccination information has been linked to people's hesitancy to get vaccinated [9, 51, 100], and previous research on effective vaccine narratives has shown that texts with high emotional arousal were more likely to leave an impression on people in terms of perceived risk than texts with neutral statistical information [9]. Resharing and mere exposure however may not automatically lead to persuasion, and the relationship between the concepts may be more nuanced. Future studies should be done to better understand the long-lasting effect of arousal on the persuasiveness of Twitter messages.

5.4 Political ideology

The effect of arousal and sentiment was moderated by the political ideology of the Twitter user sending the message. Unsurprisingly, it seems users are more likely to retweet messages that align with their own views and sentiment: very Liberal users were more likely to have messages with a positive sentiment retweeted, whereas very Conservative users were more likely to have messages with a negative sentiment retweeted.

Further, while high-arousal tweets were more likely to be retweeted regardless of political ideology, arousal had a larger effect among very Liberal users compared to moderate and Conservative users. Though prior studies on political speeches and messaging have suggested that high-arousal words appeal more to conservatives, these studies usually confounded arousal with sentiment [31, 90]: whereas negative high-arousal words, such as those used in fear rhetoric, primarily appeal to those with more conservative beliefs, the same effect has not been found for positive high-arousal words, such as those expressing excitement [90]. Further, a study focusing specifically on social media found that Liberals engage more with toxic content than Conservatives [17]. Toxic content may create more arousal, which helps explain the stronger effect of arousal among Liberals in our study. Liberals and Conservatives may also react differently to emotional information depending on the content of the information. People may act more upon information if it is a topic they are passionate about [67] and it aligns with their morals and values. A range of emotions have been expressed online about the COVID-19 pandemic [12]. There may be differences in the types of emotions and how their intensity affects different political ideologies, although this warrants further research.

5.5 Extremism of political ideology

Our results showed that overall Conservatives expressed a more negative sentiment toward the COVID-19 vaccine and that there were no differences between ideologies in terms of concreteness. However, a closer look at the nature of these relationships, as plotted in Figure 3, show that they follow a curved rather than linear trend: that is, the more extreme the ideologies, both on the Liberal and Conservative side, the more negative the sentiment and the more concrete the tweets. This indicates that it is not only worth looking at whether people are Liberal or Conservative, but to also consider the extremism of their political ideology. An important question for future work is why extreme political ideologies would express less positive views toward vaccines and use more concrete words than moderates.

Some studies have discussed how social media platforms may contribute to polarization. For example, people tend to follow accounts with whom they already agree and who further confirm and solidify their beliefs [4, 20, 76]. When people do encounter social media posts about political opponents, this tends to generate more engagement but particularly in the form of negative comments and reactions [71]. This polarization effect may sway people to form more extreme opinions online. Prior research also suggests that degree of conservatism is linked with vaccine hesitancy [10], which could explain the more negative sentiment of very Conservative individuals. Future research is warranted to understand the less positive sentiment on the very Liberal side.

5.6 Limitations

Our study shed insight into what linguistic features can impact the likelihood of message resharing. However, we do not know what impact these messages will have on offline actions, and whether they will make people more or less likely to get vaccinated. It would be worthwhile to conduct future studies looking into the impact of online messages on offline behavior.

We considered the political ideology of the Twitter user sending the message, but did not have data on the identity or ideology of the users who decided to retweet the message. People mostly follow accounts and retweet messages that are in line with their beliefs [4, 20, 76]; however, we cannot rule out that people may retweet messages from accounts they do not follow, and that contradict their viewpoint, to react or provide commentary on the message.

To measure sentiment, arousal and concreteness, we used lexicons that have been widely used standardized dictionaries in prior work. A known issue with a lexicon approach is that it only includes a limited set of terms and that relevant words in our dataset may be missed if they are not included in the lexicon. In response to this limitation of using a standardized lexicon, some studies have developed their own modified dictionaries and domain-specific approaches [50]. It would be worthwhile to conduct follow-up studies exploring other approaches and dictionaries such as the NRC lexicon [54], or to develop an extended dictionary with words or to build a repository of vaccine framings more common in vaccine discussions. Additionally, the package used to calculate sentiment scores (sentimentr) considered a window of 5 words before a polarized word, and 2 words after the polarized word to determine its sentiment. Future research may explore customizable packages and libraries that can control for different n-grams and compare its results.

A known limitation of Twitter studies is that it represents a specific demographic and may not be representative of the wider population. For example, Twitter users are more likely to identify as liberal, come from a higher socio-economic background, and the largest age group on Twitter is aged 18 to 29 [59]. Similarly, our dataset contained more Liberal users than Conservative users.

While recent changes in Twitter policies may affect data access for researchers in the future, as of the time of writing, the Twitter data used in this paper can still be accessed for a fee through the Twitter API [94]. More may be known in the coming years about how the increased closed nature of Twitter may affect data access and people's adoption of other social media platforms [35, 74].

Lastly, as previous work has shown, the specific context of a situation influences the effect of linguistic features on online message resharing, and our findings should be interpreted within the context of the COVID-19 vaccine. We thus cannot generalize our findings beyond online social media discussions on vaccines.

5.7 Implications

Twitter is a major platform to access and share health information [102]. Our study indicated that generic public health vaccine messages may not be effective for everyone in politicized contexts in the United States, and that vaccine messages could benefit from being tailored depending on the political ideology of the audience. Our paper studied message resharing of public US Twitter accounts, and our findings should be interpreted within this context. Public health campaigns can use our study findings for social media campaigns, and phrase vaccine information in a way to promote information resharing and expand its reach to a larger audience. Future research may further our understanding on the contexts in which adapting a message's sentiment, arousal and concreteness may reduce vaccine hesitancy. Evidence for message strategies to increase propagation of accurate and credible vaccine messages is needed especially given the emerging evidence that vaccine message acceptance differs by political ideology [23, 38].

First, findings suggest that more abstract vaccine messages increase retweeting of public health disseminated vaccine messages. While this finding initially may seem counterintuitive, construal level theory (CLT), a psychological proximity theory in relation to risk perception and decision-making may give insight. The most important finding from this theory is that individuals think about psychologically distant realities with an abstract mindset (high construal) while psychologically proximal realities are construed at a concrete and detailed level (low construal) [48, 91]. CLT has been expanded to reflect desirability versus feasibility with 'desirability' representing users' "why should this action be performed" (high construal) versus feasibility representing users' "how can this action be formed" (low construal). According to research, individuals put more weight on high construal when making decisions [79]. Kim and Nan [42] found that vaccine promotion messages paired with distant temporal or high construal messaging had higher intentions to vaccinate. Given that vaccination is a controversial topic, especially among those considering and who have not yet vaccinated, more abstract vaccine messaging may translate into greater vaccine message acceptance.

Second, for high-arousal and valenced vaccine messaging, messaging should be tailored depending on the political ideology of the audience. Tailoring vaccine messages in this context will more likely lead to greater message acceptance and greater resharing of promotional vaccine messages. For sentiment, results suggest that more Liberal users will reshare more positively valenced vaccine messages, while a different strategy will be needed for Conservative users. Perhaps for conservative audiences, a vaccine message may need to open with a loss framed vaccine message to have a greater chance of being retweeted [60]. Findings extend existing work on the role of sentiment on message resharing, which found effects for both positive and negative sentiment [25, 39, 77, 102]. Rather than a universal recommendation to include positive or negative wording in a message (e.g., an emphasis on the positive aspects of getting vaccinated versus the negative consequences of not getting vaccinated), its tone may have to be tailored depending on an account and its particular audience. However, for high-arousal vaccine messages, crafting high-arousal vaccine messages may more likely be shared among both Liberals and Conservatives.

Lastly, our findings inform future research on message resharing on social media. When considering situations that have been politicized, such as the COVID-19 vaccine, people's political views can moderate the effect that message features have on resharing. Considering the political ideology of Twitter users in these cases may help explain why some of their messages get retweeted more than others.

6 CONCLUSION

This study investigated how characteristics of messages related to the COVID-19 vaccine may influence users' decisions to retweet those messages. We found that the likelihood of message resharing is associated with abstract, high-arousal, and positive messages. However, the effect of arousal and sentiment are moderated by a Twitter user's political ideology. Public health vaccine communication may benefit from using these results when phrasing vaccine messaging to expand its reach to the public.

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