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Platform Cultures and Emotional Communication About Climate Change: A Comparison of Affective Language in the Climate Change Blogo- and Twittersphere

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In recent years, climate change discussions have shifted from the blogosphere to platform cultures like Twitter (now X). However, it remains unclear how this shift has influenced the emotional tone of these conversations. In this preregistered study, we explored differences in affective and emotional language usage between English-language climate change blogs and tweets. Using sentiment classifiers, we analyzed two datasets: 2,633 blog posts from 18 blogs and 167,000 climate-related tweets. Contrary to expectations, blogs scored higher than tweets across all categories of affective language (positive and negative emotions, including fear, anger, sadness, disgust, joy, and surprise). Joy and surprise were the most frequently identified emotions in both datasets. On Twitter, positive-emotional language predicted higher engagement (likes and shares) more effectively than negative language or specific emotions. However, we observed differences depending on the sentiment classifiers used (Empath, Syuzhet, and VADER). These

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findings contribute to discussions of how different platform cultures influence climate change communication and affect the overall quality of the debate.

Keywords: climate change, blogs, Twitter, emotions, platform cultures

The first climate change blogs were launched in the mid-1990s, quickly blossoming into a "blogosphere" with substantial influence on scientific, political, media, and public discourse (Lewandowsky, Oberauer, & Gignac, 2013; Nerlich, 2010; van Eck, Mulder, & Dewulf, 2019). For example, during the 2009 "climategate" episode, climate blogs led the discussion about the hacked emails, which, according to climate skeptics, suggested that climate change was a hoax (Nerlich, 2010; Schmidt, 2010). This event significantly influenced public trust and opinion (Leiserowitz, Maibach, Roser-Renouf, Smith, & Dawson, 2012).

However, over the last decade, online conversations about climate change have shifted from the blogosphere to social media. Many blogs have ceased to exist (e.g., Global Climate Scam) or do not publish blog posts as frequently as they used to (e.g., Bishop Hill). Schmidt (2019), who works for the climate science blog *RealClimate,* argues that "The social media landscape has changed beyond recognition but yet the fever swamps of duelling blogs and comment threads has just been replaced by troll farms and noise-generating disinformation machines on Facebook and Twitter" (para. 3). For comparison, Elgesem, Steskal, and Diakopoulos (2015) retrieved 1.3 million English-language blog posts in 2012, Kirilenko and Stepchenkova (2014) collected 1.8 million tweets in five languages in 2012–2013, and Littman and Wrubel (2019) gathered 39.63 million English-language tweets in 2017–2019, all with climate change or related search terms. While the blogosphere has gained less traction, the Twittersphere (now X) has a "global reach and growing number of users and posts," which makes the platform "too important now to ignore" (Veltri & Atanasova, 2017, p. 724).

To date, how this shift from the blogosphere to social media (and especially Twitter) has affected the nature of the public debate around climate change is an open question. Research has looked at how platforms have their own distinct technological features, users, and communication practices (Pearce, Holmberg, Hellsten, & Nerlich, 2019; Yarchi, Baden, & Kligler-Vilenchik, 2020). For example, each platform may facilitate different polarization dynamics (Yarchi et al., 2020). Therefore, more research is needed to investigate how different platform cultures (i.e., communication practices and technical features) shape climate change communication (Pearce et al., 2019).

The blogosphere and Twittersphere differ in various important ways. First, blog posts are generally characterized as long-form content, typically between 300 and 600 words (Van Eck et al., 2019). In contrast, tweets are characterized as short-form content, currently limited to 280 characters. Second, the style of writing is different. Bloggers' tone is generally characterized as opinionated and considerate (Fischer, 2018; Van Eck et al., 2019), while Twitter was designed as a platform to update users' friends about their day-to-day activities (Kirilenko & Stepchenkova, 2014). Third, bloggers can moderate user comments themselves (van Eck, Mulder, & Dewulf, 2020), whereas users cannot control the interactions on Twitter. Fourth, blog posts are updated in reverse chronological order, meaning audiences can scroll through a single user's timeline (Garden, 2013; Van Eck et al., 2019), while Twitter's timeline is arranged with a curation algorithm that "sorts, filters, and supplements personalized content" (Bandy & Diakopoulos, 2021, p. 78). The latter also implies that blog users usually intentionally visit a specific blog (van Eck, Mulder, & van der Linden, 2020b), while Twitter users could unintentionally be exposed to climate and nonclimate-related content, for example, through the platform's retweet function. Lastly, blogs are updated at the discretion of the blogger (Van Eck et al., 2019), while Twitter updates tweets minute-by-minute (Thelwall, Buckley, & Paltoglou, 2011).

Moreover, both platforms are used by different segments of society. Previous research indicates that audiences of climate change blogs are predominantly male, 55 years or older, highly educated, and highly engaged (Van Eck et al., 2020b, 2020a). Other research shows that Twitter users in the United Kingdom are also mostly male, highly educated, younger, and more attentive to politics than the general population (Mellon & Prosser, 2017).

Each platform facilitates different polarization dynamics (Yarchi et al., 2020). Previous research has shown that various forms of positional, interactional, and affective polarization dynamics are present in the climate change blogosphere (van Eck, 2021). For example, patterns of polarization are visible in the linking behavior (Elgesem et al., 2015; Sharman, 2014), topics (Elgesem et al., 2015), discourses of bloggers (Van Eck & Feindt, 2021), interactions of commenters (van Eck et al., 2020), and blog consumption patterns of audience members (Van Eck et al., 2020b). Previous research has also shown that polarization dynamics are visible in the Twittersphere. For example, polarization dynamics are present in semantic networks (Pearce, Holmberg, Hellsten, & Nerlich, 2014; Williams, McMurray, Kurz, & Hugo Lambert, 2015) and the framing of discussions (Moernaut, Mast, Temmerman, & Broersma, 2020). Thus, while we know that each platform has its own distinct technological features, users, communication practices, and cultures (Pearce et al., 2019; Yarchi et al., 2020), it is not clear how the respective platform cultures shape, enable, or constrain emotional communication about climate change.

In the present study, we focus on one dimension of platform culture: the platform's use of affective and emotional language. *Affect* refers to general positive or negative feelings, whereas *emotions* refer to distinct emotions, which are intense and short-lived, more complex, and less subtle (Smith & Leiserowitz, 2012). Our focus is motivated by the growing body of evidence on the important role of affect and emotions in shaping climate change risk perceptions and productive climate change engagement (Gustafson et al., 2020; Leiserowitz, 2006; Salama & Aboukoura, 2018; Schneider, Zaval, & Markowitz, 2021; Van der Linden, 2015; Xie, Brewer, Hayes, McDonald, & Newell, 2019). For example, van Eck et al. (2020a) showed that affect is the most influential predictor of variances in blog audience members' climate change risk perceptions, being more important than other predictors such as knowledge and political ideology. Furthermore, Veltri and Atanasova (2017) showed that climate change tweets that arouse emotions are more likely to be shared, providing an opportunity for productive climate change engagement. Finally, while recent research on the climate change Twittersphere indicates that negative affective language is present more than positive affective language (Dahal, Kumar, & Li, 2019; Effrosynidis, Sylaios, & Arampatzis, 2022; Loureiro & Alló, 2020; Tyagi, Uyheng, & Carley, 2021), little evidence is available about affect and emotions in the climate change blogosphere.

Overall, if one platform uses more (or less) affective language, this might have implications on how individuals engage with the issue of climate change, depending on where they obtain their information. Therefore, investigating affective language in the blogo- and Twittersphere is important, as it provides insight into how platform cultures shape, enable, or constrain climate change communication and the quality of the debate. Thus, the main research question of the current research is as follows:

RQ1: What are the differences in affective and emotional language in the English-language climate change blogosphere and Twittersphere?

Theoretical Framework

Emotional content may elicit affective responses that boost engagement with climate change discourse (Bilandzic, Kalch, & Soentgen, 2017). However, Chapman, Lickel, and Markowitz (2017) note that scientists and practitioners should not view emotions as a magic bullet that guarantees climate change engagement, as much is unknown about the impact of affective language use over time (e.g., on opinion formation). Instead, emotions ought to be viewed as "one integral component of a cognitive feedback system guiding response to challenging decision-making problems" (Chapman et al., 2017, p. 850).

Bloggers' and Twitter users' emotional state may influence how they write a blog post or tweet. Moreover, since affect is a strong predictor of how individuals shape their climate change risk perceptions (Van der Linden, 2015; Van Eck et al., 2020a; Xie et al., 2019), tweets and blog posts with affective language will likely elicit stronger affective responses among their readers than those without. Van der Linden (2014) discusses how "an '*affective'* response is usually defined as a fast, associative, and automatic reaction that guides information processing and judgment" (p. 430; emphasis in original). Blog posts are considerate long-reads that usually require several hours to write and edit, partly because climate change bloggers are cautious about making errors (Van Eck et al., 2019). In contrast, tweets are short-form content that allow users to write and post content quickly, without necessarily requiring much forethought. Thus, Twitter users may rely more on fast, associative, and automatic reactions when publishing tweets compared with bloggers. Accordingly, we posit that tweets are more likely to make use of affective language than blog posts:

H1: In the climate change Twittersphere, affective language is used more frequently than in the climate change blogosphere.

Generally, both positive and negative emotions can play an important role in people's responses to climate change. Positive emotions can motivate people to engage with climate change, whereas negative emotions can motivate people to be on "high-alert" (Salama & Aboukoura, 2018). Negative affective evaluations of climate change predict higher climate change risk perceptions (Leiserowitz, 2006; Smith & Leiserowitz, 2014; Van der Linden, 2015; Van Eck et al., 2020a; Xie et al., 2019). However, it is important to couple content that elicits negative emotions with pragmatic solutions on how climate change can be addressed if one wants to promote engagement with climate change discourse or solutions (Moser & Dilling, 2011). While evidence suggests that positive emotions can indeed support productive climate change engagement, the relationship is complex, and increasing positive emotion does not automatically lead to greater engagement (Schneider et al., 2021).

Little research is available that looks at affective language in the blogosphere. The climate change blogosphere is characterized by stark polarization between climate "skeptics" and the climate "mainstream," which includes scientists and climate activists (Elgesem et al., 2015; Sharman, 2014; Van Eck & Feindt, 2021). Generally, polarizing communication is characterized by affective polarization. This is also true for interactions in climate change blog comments, where negative identity labels are deployed by both sides (van Eck et al., 2020). Moreover, both climate scientists and skeptics are concerned with "correcting" the scientific findings and methods of the other side (Van Eck et al., 2019; Van Eck & Feindt, 2021). Climate skeptics and climate activists portray the other side as villains and use negative rhetoric (Van Eck & Feindt, 2021). It is therefore plausible to assume that the sentiment in climate change blog posts is principally negatively valanced.

More research is available that analyzes affective language in the Twittersphere by distinguishing between positive and negative emotions. While some studies showed that climate change tweets are predominantly neutral (Veltri & Atanasova, 2017; Walter, Lörcher, & Brüggemann, 2019), the majority of existing literature indicates that negative affective language is present more than positive affective language (Dahal et al., 2019; Effrosynidis et al., 2022; Loureiro & Alló, 2020; Tyagi et al., 2021). For example, Dahal et al. (2019) found that climate change discussions on Twitter are negative overall, suggesting that users mostly respond negatively to current affairs, such as political and extreme weather events. Moreover, they showed how the polarized sides both used derogatory language. Similarly, Tyagi et al. (2021) provided evidence for affective polarization in climate change Twitter discourse between "disbelievers" and "believers," showing how disbelievers expressed more hostility toward believers. In a similar vein, Effrosynidis et al. (2022) showed how users in North America, Oceania, and some other countries known for climate skepticism held more negative attitudes about climate change than people in other countries. In contrast, Loureiro and Alló (2020) found that climate change tweets in the United Kingdom were less negative than tweets in Spain. Furthermore, tweets in the news segment about COP15 are more likely to go viral if they contain negative-emotional content (Hansen, Arvidsson, Nielsen, Colleoni, & Etter, 2011). Thus, based on previous literature, we posit that the chances are greater that tweets contain negative affective language instead of positive affective language. Therefore, we hypothesize the following:

H2a: *Negative-emotional language is used more frequently than positive-emotional language, both in the climate change blogosphere and Twittersphere.*

H2b: *The ratio of negative to positive-emotional language is higher in the climate change Twittersphere than in the blogosphere.*

More specifically, and beyond categorizing emotions as either "positive" or "negative," it is useful to investigate which distinct emotions are prevalent in the language in climate change blog posts and tweets. Previous research has shown that *fear* is generally ineffective in fostering climate change engagement, as individuals likely feel overwhelmed and distance themselves from the issue (Moser & Dilling, 2011; O'Neill & Nicholson-Cole, 2009). Furthermore, Chu and Yang (2019) found that anger, anxiety, and hope had a stronger impact on climate mitigation actions and policy support than fear, guilt, and shame. However, little experimental evidence is available to make generalizable claims about the role of distinct emotions in climate change engagement (Chapman et al., 2017).

Similarly, limited evidence is available about the use of distinct emotions in climate change blog posts. Qualitative analyses focusing on how bloggers construct their posts showed that they communicate both fear-inducing and hopeful messages (Van Eck et al., 2019; Van Eck & Feindt, 2021). However, more research is available on the use of distinct emotions in tweets. Using a sentiment analysis approach, Cody, Reagan, Mitchell, Dodds, and Danforth (2015) found that sentiment depends on specific words. For example, natural disasters can decrease expressions of happiness, whereas climate rallies can increase them. Veltri and Atanasova's (2017) sentiment analysis of climate change tweets found that anger was the most frequently identified emotion. Loureiro and Alló (2020) found that climate change tweets in the United Kingdom mostly contained language related to trust, fear, and anticipation, whereas tweets in Spain were more likely to contain fear-evoking language. Overall, especially in the blogosphere, much remains unknown about which distinct emotions are prevalent in online content. Therefore, we ask the following exploratory questions:

SQ1: *Which emotions are the most prevalent in the language of climate change blog posts and tweets?*

SQ2: *What kind of affective language is used by climate-skeptical and climate-mainstream blogs?*

Finally, research has shown that the use of moral-emotional language in social media content correlates with engagement and virality potential (Brady et al., 2017; Hansen et al., 2011; Rathje, van Bavel, & van der Linden, 2021). In other words, emotional language use is a predictor of how many times a piece of social media content is liked or shared. Within the context of climate change discussions on social media, Hansen et al. (2011) found that negativity was a strong predictor of retweeting COP15 news segment tweet. Therefore, we also examine whether these findings can be replicated within the context of social media discussions specifically about climate change:

SQ3: *Does the use of affective language predict engagement with social media content about climate change?*

Methods

We preregistered this study on AsPredicted (aspredicted.org/myq7-6myk.pdf). For deviations from the preregistration, see the Data Analysis section. All data, analyses, and visualization scripts, as well as supplementary information, can be found on OSF (https://osf.io/g45pm/).

Data Collection

We aimed to collect two comparable datasets of tweets and blog posts. For tweets, we used the open-access "Climate Change Tweets IDs" dataset (Littman & Wrubel, 2019), which includes 39.63 million tweet IDs collected via the Twitter Stream API using keywords such as "#climatechange," "#globalwarming," and "#climatehoax." The tweets were posted between September 21, 2017 and May 17,

2019. Using a Python script, we retrieved tweet content via the Twitter API (v1) and filtered out retweets, resulting in a dataset of 8,192,222 tweets. However, there were a data gap between January 7, 2019, and April 17, 2019.[4]

We aimed to collect a comparable dataset of blog posts using the same keywords and timeframe. Initially, 172 climate change blogs were identified through expert knowledge and snowball sampling. Blogs were selected based on these preregistered criteria: (1) a blog section with dated entries in reverse chronological order; (2) at least five posts between October 1, 2017 and September 30, 2018; (3) hosted on WordPress or Blogger (Elgesem et al., 2015); (4) written in English; and (5) at least 75% of the content focused on climate change. Of the 70 blogs that met these criteria, we collected posts from WordPress using its API. However, the Blogger API was malfunctioning, and some WordPress blogs returned "404" or "406" errors. After data collection, we filtered posts using preregistered keywords ("climate change," "global warming," "climate hoax," etc.) to align with the tweet dataset. The final dataset included 2,633 posts from 18 blogs: 11 by climate skeptics, three by climate scientists, one by a climate journalist, and three mainstream blogs (see OSF for details).

Data Analysis

First, we preprocessed both datasets using Python scripts (see OSF page). For tweets, we removed @usernames, URLs, and nonalphabetic characters. For blog posts, we extracted plain text from the HTML code using the BeautifulSoup package and then applied the same cleaning process as for the tweets.

We then ran the Empath Python package (version 0.89) on the full dataset. Empath is a tool that can generate and validate new lexical categories. These categories can be used to analyze text. The developers of Empath explained it as follows:

> Empath learns word embeddings from 1.8 billion words of fiction, makes a vector space from these embeddings that measures the similarity between words, uses seed terms to define and discover new words for each of its categories, and finally filters its categories using crowds. (Fast, Chen, & Bernstein, 2016, p. 11).

Empath was validated against other dictionary-based language analysis methods, such as the Linguistic Inquiry Word Count (LIWC), and it was shown to perform similarly or better on various metrics (Fast et al., 2016). Empath dictionaries were trained on a series of corpora, including news articles and Reddit posts, making them suitable for use in social media research (Klein, Clutton, & Dunn, 2019).

In this study, we used only preexisting Empath categories. More specifically, we tested H1 by looking at both the "Negative_emotion" and "Positive_emotion" categories. We also used these categories for hypotheses H2a and H2b but applied them separately rather than combined. Lastly, based on Ekman's (1992) "basic emotions," we investigated subquestion 1 using the Empath categories "anger," "fear,"

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[4] This is a potential limitation of our study and our findings; we are, unfortunately, unable to check if the results hold up for content published during the missing time period.

"disgust," "joy," "sadness," and "surprise." The Empath analysis provided us with scores for each category. These scores indicated how many times a category was counted in the text. While not preregistered, we log-transformed these variables before the analysis.

Additionally, as a (nonpreregistered) robustness check for Hypotheses H1 and H2b, we supplemented our Empath analyses with two different sentiment classifiers: the R package "Syuzhet" and VADER. Syuzhet has rapidly become the most prominent sentiment classifier available within the R framework (Kim, 2022), and, like the Linguistic Inquiry and Word Count or LIWC (Pennebaker, Booth, Boyd, & Francis, 2015), relies on lexicons (i.e., dictionaries) for emotion classification (Jockers, 2015). The package was designed to extract sentiments from prose, making it suitable for longer-form text analysis (e.g., blogs) but less so for short-form content (e.g., Tweets). Syuzhet, like Empath, can identify the use of distinct emotions in the body of text. Many of the same categories listed above are available, including positive and negative emotions, anger, fear, disgust, joy, sadness, and surprise. Analyzing the use of these emotions under a different classifier allows us to see whether the results are consistent across classification methods. However, Syuzhet has been criticized for being unable to deal with negations (Naldi, 2019) and for being less accurate than machine learning-based approaches (such as Empath and VADER) (Kim, 2022). Nonetheless, the package is widely used and can provide useful additional insights into the use of emotions in climate blogs and Twitter content. Again, we log-transformed these variables (not preregistered). See Figure S4 for intercorrelations between Empath and Syuzhet scores per emotion category.

VADER is a lexicon- and rule-based sentiment classifier widely used in the computational social sciences for sentiment analysis (Hutto & Gilbert, 2014). VADER was specifically designed to detect emotions (positive, negative, and overall emotionality, but not distinct emotions) in microblog social media content (e.g., Twitter). Hutto and Gilbert (2014) found that VADER outperforms other classifiers and human raters and generalizes well to other forms of content. We therefore included VADER as a third sentiment classifier (again log-transformed, not preregistered).

To ensure that both datasets had comparable word counts, we used 2,633 blog posts (averaging 954 words each) and approximately 167,000 tweets (averaging 15.1 words) to achieve similar total word counts ([2,633 * 954]/15). To confirm that the 167,000 tweets were representative of the full dataset (N = 8,192,222), we randomly sampled five subsets of 167,000 tweets and conducted a one-way Welch's ANOVA using Empath categories as dependent variables. No significant differences were found across the samples for any outcome variables (see Table S2 and Figure S1), indicating that the subset was reasonably representative.

We preregistered that H1 would be tested with independent samples Welch's t-tests, as the Twitter and blog datasets have unequal variances and sample sizes. However, since this method could not account for the substantial word count differences between tweets and blogs, we realized it was not appropriate (though these analyses are provided in the supplement for completeness; see Tables S3 and S4). Instead, we used linear mixed models in R (using the "lme4" package), with emotional categories (negative/positive-emotional language, anger, disgust, fear, joy, sadness, surprise) as dependent variables, dataset (Twitter/blogs) and word count as fixed effects, and user/blog ID and publication month as random effects: lmer([affective language category] ~ Dataset [Twitter/blogs] + word_count + (1 | userid) + (1 | month)).

As preregistered, H2a was tested by running a Wilcoxon signed-rank test on the Empath, Syuzhet, and VADER categories "Positive_emotion" and "Negative_emotion" for both datasets. We also ran a series of (nonpreregistered) Bayesian analyses for the sake of robustness. We tested H2b by creating a variable representing the ratio of positive versus negative language used in each post (i.e., subtracting the score for negative language from the score for positive language), and running a linear mixed model with this new variable (positive/negative ratio) as the dependent variable (for each of the three sentiment classifiers), with the other model specifications the same as for H1 above.

We initially preregistered that we would test subquestion 1 (SQ1) using one-way ANOVAs to compare anger, disgust, surprise, joy, sadness, and fear in the blog and Twitter datasets. However, we found that pairwise comparisons via Wilcoxon signed-rank tests were more appropriate. For SQ2, which examined differences between climate-mainstream and climate-skeptical blogs, we did not preregister an analysis plan. Instead, we applied Student's, Welch's, and Bayesian t-tests, using the blog's stance (mainstream or skeptical; see Table S1 for categorization) as the independent variable and "Negative_emotion," "Positive_emotion," and distinct emotions (anger, etc.) as the dependent variables.

Finally, although we were unable to collect engagement metrics (such as the number of reads or page visits) for the blogs, our Twitter dataset featured the number of retweets and "favorites" for each tweet. To answer subquestion 3 (SQ3), we followed the method for analyzing social media engagement proposed by Kyrychenko, Brik, van der Linden, and Roozenbeek (2024): We ran a linear mixed model with engagement (log-transformed to deal with skewness) as the independent variable, affective language categories as fixed effects, and month of posting, user ID, and word count as random effects. However, as a limitation, we note that we could not obtain each Twitter user's follower count (because of changes in the Twitter API, this information was also unavailable post hoc), which was included in the analyses conducted by Kyrychenko et al. (2024), who also observed that follower count is a strong predictor of engagement. Thus, we consider this analysis preliminary.

All analyses were conducted in R (version 4.2.3). Our data cleaning, analysis, and visualization scripts, as well as all supplementary information, are available on our OSF page: https://osf.io/g45pm/.

Results

Testing H1, a linear mixed model with negative emotion as the DV and dataset (Twitter/blogs) and word count as fixed effects (with user ID and month of posting as random effects) shows that blogs use significantly more negative language than tweets, b = -0.0133 [-0.0139, -0.0127], $p < .001$. The same is the case for positive language, albeit with a much smaller coefficient, b = -0.0032 [-0.0038, -0.0026], $p < .001$. Similarly, we find that language related to anger (b = -0.0008 [-0.0011, -0.0005], $p < .001$), disgust (b = -0.0008 [-0.0011, -0.0006], $p < .001$), fear (b = -0.0003 [-0.0005, -0.0001], $p = .014$), joy (b = -0.0067 [-0.0073, -0.0061], $p < .001$), sadness (b = -0.0006 [-0.0009, -0.0004], $p < .001$), and surprise (b = -0.0082 [-0.0090, -0.0075], $p < .001$) are used significantly more in blogs compared with tweets.

Overall, these results trend in the direction of blogs using more affective language than tweets, contradicting H1. See Table S5 for full model overviews.[5]

These somewhat odd results (with many of the coefficients near 0, despite low p-values) may be explained by our use of Empath as a sentiment classifier, which may not be well-suited for our specific dataset (as the classifier was trained on Reddit posts and *New York Times* articles, not tweets or blogs). Therefore, we re-ran the above analyses using the R package Syuzhet, which relies on a different emotion classification method than Empath. The results are similar: All categories of affective language are used significantly more often in blogs than in tweets, including negative language (b = -0.0373 [-0.0383, -0.0364], $p < .001$), positive language (b = -0.0560 [-0.0570, -0.0550], $p < .001$), anger (b = -0.0366 [-0.0379, -0.0353], $p < .001$), disgust (b = -0.0337 [-0.0351, -0.0324], $p < .001$), fear (b = -0.0451 [-0.0466, -0.0435], $p < .001$), joy (b = -0.0456 [-0.0471, -0.0441], $p < .001$), sadness (b = -0.0349 [-0.0359, -0.0338], $p < .001$), and surprise (b = -0.0399 [-0.0414, -0.0385], $p < .001$). See Table S6 for the full model tables. These results offer further support *against* H1, in that blogs use *more* affective language than tweets in climate change discussions.

However, for VADER, we find no differences between Twitter and blogs for either positive emotionality (b = -0.0001 [-0.0205, 0.0204], p = 0.995) or negativity (b = -0.0024 [-0.0206, 0.0158], p = 0.796), although we do find a (weak) effect for overall affective language such that blogs use more affective language than tweets (b = -0.0638 [-0.1227, -0.0048], p = 0.034). See Table S11.

Concerning H2a, we show the results of the Wilcoxon signed-rank tests for the "Negative_emotion" and "Positive_emotion" categories separately for blogs and tweets in Table 1. We find contradictory results across sentiment classifiers. For Empath, negative-emotional language is used significantly more than positive emotions on both Twitter and in climate blogs. This is the reverse for Syuzhet and VADER. These results do not allow us to draw firm conclusions for or against H2a.

To test hypothesis H2b, we ran a linear mixed model (with the same specification as mentioned above) with the ratio of positive to negative language as the independent variable. Doing so shows that for Empath, the ratio of positive to negative language is significantly higher in tweets compared with blogs, b = 0.0099 [0.0092, 0.0105], $p < .001$ (see Table S5). However, this is the reverse for the Syuzhet classifier, b = -0.0156 [-0.0164, -0.0147], $p < .001$ (see Table S6), and we find no significant relationship for VADER (b = 0.0021 [-0.0282, -0.0325], p = 0.891, Table S11), again allowing for little inference with respect to H2b.

[5] We note that we obtained singular fit warnings for the "negative emotion," "anger," "fear," "joy," and "sadness" Empath models (see Table S5), and also for the "positive emotion," "anger," and "joy" categories for Syuzhet, and finally the "positive emotion" category for VADER. This is likely either due to extremely small variance in the random effects, or (more likely) because the data is not sufficiently informative to say if the estimate is sufficiently different from 0; we therefore urge caution with the interpretation of these findings.

Table 1. Wilcoxon Signed-Rank Tests and Bayesian T-Tests for Negative_emotion vs. Positive_emotion, by Dataset and Sentiment Classifier (H2a).

Variables			**Statistic**	**±%**	**p**	**Effect size**
<u>Twitter</u>						
Positive emotion (Empath) (*M* = 0.000956, SD = 0.00468)	**Negative emotion** (Empath) (*M* = 0.00159, SD = 0.00521)	BF_{10}	Inf	0.00		
		Wilcoxon W	9.19e+07		**< .001**	-0.1209
Positive emotion (Syuzhet) (*M* = 0.00362, SD = 0.00460)	Negative emotion (Syuzhet) (*M* = 0.00328, SD = 0.00484)	BF_{10}	1.65e+90	5.24e-96		
		Wilcoxon W	3.08e+09		**< .001**	-0.0153
Positive emotion (VADER) (*M* = 0.0853, SD = 0.107)	Negative emotion (VADER) (*M* = 0.0691, SD = 0.100)	BF_{10}	Inf	0.00		
		Wilcoxon W	3.83e+9		**< .001**	0.1412
<u>Blogs</u>						
Positive emotion (Empath) (*M* = 0.0538, SD = 0.076)	**Negative emotion** (Empath) (*M* = 0.0642, SD = 0.076)	BF_{10}	1.46e+14	1.79e-18		
		Wilcoxon W	944,047		**< .001**	-0.270
Positive emotion (Syuzhet) (*M* = 0.145, SD = 0.123)	Negative emotion (Syuzhet) (*M* = 0.114, SD = 0.106)	BF_{10}	2.03e+187	1.51e-191		
		Wilcoxon W	2.79e+06		**< .001**	0.638
Positive emotion (VADER) (*M* = 0.0844, SD = 0.0354)	Negative emotion (VADER) (*M* = 0.0712, SD = 0.0414)	BF_{10}	1.21e+30	2.40e-34		
		Wilcoxon W	2.24e+06		**< .001**	0.317

Note. Effect size is displayed as rank biserial correlation. P-values are uncorrected for multiple comparisons. See Table S4 for descriptive statistics.

For subquestion SQ1, we conducted a series of Wilcoxon signed-rank tests on the anger, disgust, surprise, joy, and fear Empath categories, separately for the blog and Twitter datasets. The results are visualized in Figure 1 (see Table S7 for more details). In blog posts, of the six basic emotions, language related to surprise is used the most, before joy, anger, sadness, and finally disgust and fear. The same pattern is found on Twitter, with surprise and joy being used the most, before sadness, fear, anger, and finally disgust. All between-group comparisons are significant (all *p*-values < .020), except between disgust and fear for the Twitter dataset (p = .469). When correcting for multiple comparisons, the comparisons of fear–sadness (Twitter), anger–sadness (blogs), and disgust–fear (blogs) are no longer significant.

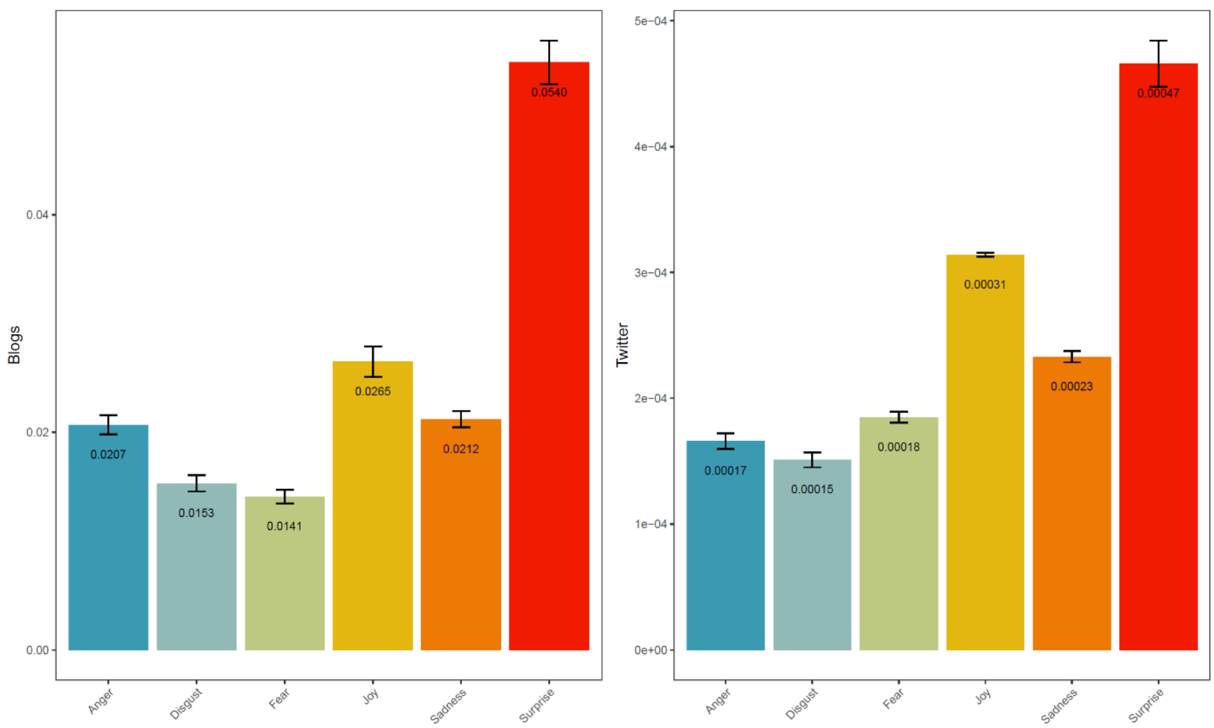

Figure 1. Bar graphs for anger, disgust, fear, joy, sadness, and surprise, separated by dataset. Y-axis shows empath scores. Error bars represent standard error.

The results of Welch's *t*-tests along with Student's and Bayesian t-tests for our exploratory analysis of affective language use in climate-mainstream versus climate-skeptical blogs (SQ2) can be found in Supplementary Table S8; see Table S9 for descriptives. Briefly put, we find that only language related to "joy" is used significantly more in mainstream blogs than in skeptical blogs (p < .001, BF_{10} = 19.985). All other emotion classifiers show either no or very weak between-group differences (all BF_{10} < 1.891). These results are again not highly informative with respect to the differences in the use of different types of affective language in climate-mainstream and climate-skeptical blogs.

Finally, to answer subquestion 3 (SQ3), we ran a linear mixed model with engagement (the log-transformed sum of retweets and likes; see Kyrychenko et al., 2024) as the independent variable, the affective language categories as fixed effects, and user ID, month of posting, and word count as random effects. The results for Empath and Syuzhet are shown in Figure 2 (see also Table S10). We find that both classifiers show that positive-emotional language is the most robust predictor of Twitter engagement. This shows that, contrary to research finding a robust association between negative and moral-emotional language and social media engagement (e.g., Brady et al., 2017; Rathje et al., 2021), *positive* language might be a better driver of engagement in the context of climate change discussions on Twitter (Kyrychenko et al., 2024).

However, we again note substantial differences between the two classifiers, with only "surprise" being positively associated with engagement for Empath, and negative language being negatively associated. In contrast, negative language shows no association with engagement for Syuzhet, whereas anger and sadness show positive associations, and disgust, fear, and surprise show negative associations. Furthermore, when replicating the below analysis (for positivity, negativity, neutral language, and overall affective language use) using VADER (see Figure S3 and Table S12), we find only a significant positive association between *overall* affective language use and engagement, whereas positive, negative, and neutral language individually are significantly and *negatively* associated with engagement. Overall, these results are again somewhat contradictory; we therefore make no strong inferences concerning how affective language use drives engagement on Twitter within the context of climate change discussions.

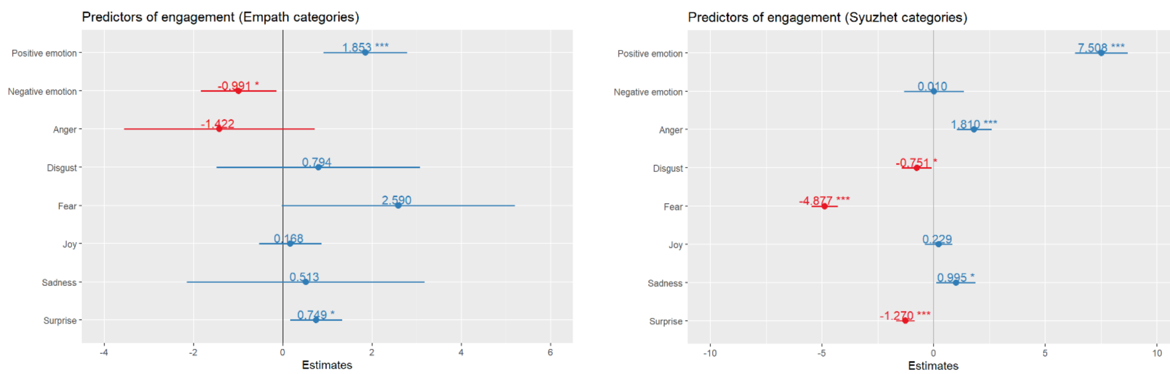

Figure 2. Affective language categories as predictors of Twitter engagement.

Note. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. See also Table S10. See Figure S5 and Table S12 for the results for the VADER classifier*.*

Discussion

In recent years, online conversations about climate change have shifted from the blogosphere to Twitter (now X). Researchers are increasingly examining how platform cultures influence climate change communication (Pearce et al., 2019). Studies highlight the crucial role of affect and emotions in shaping perceptions of climate change risks and fostering engagement with climate action (e.g., Salama & Aboukoura, 2018; Schneider et al., 2021). This study investigates the dynamics of affective and emotional language in the English-language climate change blogosphere and on Twitter.

First, contrary to our expectations, we did not find support for our first hypothesis (H1) that Twitter discussions involve the use of more affective language than climate-related blog posts. Instead, we found support for the opposite, namely that (especially negative) affective language is used *more* on blogs than on Twitter. This finding is incongruent with other work on how distinct platform cultures shape different climate change communications (Pearce et al., 2019). Prior work suggests that individuals may engage with climate change discussions and shape their climate change risk perceptions more strongly on Twitter than on blogs (Van Eck et al., 2019), possibly because of the increased presence of various kinds of affective language on social media platforms (Gustafson et al., 2020; Leiserowitz, 2006; Salama & Aboukoura, 2018;

Schneider et al., 2021; Van der Linden, 2015; Xie et al., 2019). Another possibility is that the prevalence of negative language on blogs (over Twitter) reflects the generally hostile and polarized climate change debate (Dahal et al., 2019; Effrosynidis et al., 2022; Tyagi et al., 2021), especially considering the high number of climate-skeptical blog posts included in our dataset. However, contrary to previous findings (e.g., Brady et al., 2017; Rathje et al., 2021), we find that negative emotions especially play a comparatively smaller role in Twitter climate change discussions than on blogs. It is possible that these dynamics are specific to climate change discussions (and are reversed when looking at social media discussions as a whole, regardless of the topic). We do not make strong claims as to whether this is the case because our data are unable to speak to causal dynamics. Future research may yield additional insights into whether this finding is robust, for instance, in different languages and cultures, or over time.

Second, we find mixed support for our hypothesis (H2a) that negative language is more prevalent than positive language on Twitter and blogs. Our hypothesis was supported by our preregistered classifier (Empath) but not by two others (Syuzhet, VADER). Classifiers varied in emotional prevalence and the extent to which emotions drive engagement in our Twitter dataset. For example, anger predicts higher Twitter engagement using the Syuzhet classifier, but not for Empath, and fear is negatively associated with engagement for Syuzhet, but not significantly for Empath. Surprise is *positively* associated with engagement for Empath, but *negatively* for Syuzhet. For VADER, we only find a (small) positive association between overall affective language and engagement, but *negative* associations for positive and negative language individually. These discrepancies are difficult to reconcile and may stem from differences in classifier design: Empath relies on machine learning, using a dataset of New York Times articles and Reddit posts; Syuzhet is dictionary-based, tailored for sentiment in prose-like novels; and VADER is lexicon- and rule-based, designed specifically for sentiment in social media content, particularly microblogs like Twitter/X. We note that the respective Empath and Syuzhet categories are all significantly correlated (all ps < .001, Spearman's rs > .28, see Figure S2). We therefore make no strong claims with respect to the use of most emotions (with the exception of positivity, see below) and their predictiveness of engagement or overall prevalence.

However, our supplementary analysis of the drivers of Twitter engagement shows that, in two of three classifiers used (Empath and Syuzhet), *positive*-emotional language is the most robust predictor of what Twitter users like and share when it comes to climate discussion. This finding contradicts other research (Brady et al., 2017; Rathje et al., 2021), which has generally found negative-emotional language to be a robust predictor of social media engagement. In contrast, Ferrara and Yang (2015) find that exposure to positive content led social media users to post more positive content themselves, which the authors call a form of emotional contagion. Positivity may be a more prominent emotion than negativity in the climate Twittersphere, which may drive a positive feedback loop. We are unable to settle this debate in the present study, in part because positivity was *negatively* associated with engagement when using the VADER classifier (see Figure S3). Future research should explore how technology, user behavior, and communication practices influence emotional expression online.

Third, and again according to expectations (H2b), we find that positive (or at least nonnegative) emotions, such as joy and surprise, are more common than negative emotions, such as fear, anger, disgust, or sadness, both on Twitter and in climate blogs. Again, these findings disagree with Veltri and Atanasova (2017), for example, who showed that anger was the most frequent emotion in climate debates on Twitter.

Our findings may reflect the broader dynamics of persuasive communication. Previous research has shown that fear-based messaging is especially ineffective in fostering climate change engagement if the message is not coupled with pragmatic solutions (Moser & Dilling, 2011; O'Neill & Nicholson-Cole, 2009). Therefore, it is possible that communicators in the climate change sphere generally prefer positive over negative messaging strategies. However, there is still little experimental evidence available to make definitive claims about the role of specific emotions in climate change engagement, such as fear (Chapman et al., 2017).

Fourth, we find no consistent results as to whether climate-mainstream or climate-skeptical blogs use more affective language, possibly because of the relatively low number of climate-mainstream blog posts included in our dataset. Future research may investigate whether climate-mainstream bloggers' are more emotionally involved with the issue of climate change than climate-skeptical bloggers.

Overall, our study may provide insight into the differences in affective language in the English-language climate change blogosphere and Twittersphere. However, research on this topic is still in its infancy. Therefore, more research is needed that investigates (a) the use of affective language on other online platforms, such as Facebook, and across issues (Bossetta & Schmøkel, 2023; Waterloo, Baumgartner, Peter, & Valkenburg, 2017); (b) readers' perceptions of affective and emotional climate communication (Bossetta & Schmøkel, 2023); and (c) how internal emotions of individuals shape climate change blog posts and tweets.

Concerning practical recommendations, climate change communicators may carefully consider which platforms they use for their engagement strategies, as each platform has its own platform culture that affects communication efforts (Pearce et al., 2019). Moreover, it is crucial that communicators strategically write their emotional content to align the desired communication goals with the audiences' needs (Chapman et al., 2017; Schneider et al., 2021). Chapman et al. (2017) note that "an audience-focused approach views the mix of emotions evoked in climate change communication as a factor to be understood rather than something that simplistically defines a particular communications strategy or piece of climate change communication as 'good' or 'bad'" (p. 852).

This research has several limitations. First, we found mixed results when using different sentiment classifiers (Syuzhet, Empath, and VADER), with some effects reversed depending on the classifier. This discrepancy may arise because one or more classifiers are not well-suited for our data, leading us to approach our findings with caution and to recommend further research into these questions. Second, our analysis included only 18 climate blogs, and it is unclear how well these blogs represent the entire climate change blogosphere. However, since we selected these blogs based on explicit and prespecified inclusion criteria, we are confident that they are central to the discourse. Some blogs dominated the dataset by publishing more posts, which could skew the results. Yet, this high frequency of publication might also make these blogs more representative of climate change discourse since they likely engage more frequently with the topic. Third, although we aimed to collect similar datasets of tweets and blog posts based on metrics like word count and discussed topics, substantial differences likely exist between them, which may affect our results. Future research might examine affective language separately on each platform. Fourth, we were unable to account for who posted the climate-related tweets in our Twitter dataset. The results could be skewed by a disproportionate number of bots or nongenuine content, which is challenging to mitigate because of privacy concerns. Lastly, our research is specific to the English language and the United States, so we urge caution in generalizing our findings to other contexts.

Conclusion

In this study, we have sought to provide insight into how the shift from the climate change blogosphere to the Twittersphere has affected climate change communication in terms of affective and emotional language use. Contrary to our expectations, we found that more affective language is used in the climate change blogosphere than on Twitter, with inconsistent results as to whether positive or negative-emotional language is more prevalent on either platforms (depending on the sentiment classifier used). In addition, we find that positive language is the most robust predictor of engagement (e.g., likes, shares) on Twitter, compared with negative language and other emotions (e.g., fear, anger). Our findings add to a growing body of knowledge on how platform cultures shape, enable, or constrain emotional and affective climate change communication and affect the quality of the debate.

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