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Convergence or divergence? A cross-platform analysis of climate change visual content categories, features, and social media engagement on Twitter and Instagram

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A B S T R A C T

Advocacy organizations increasingly leverage social media and visuals to communicate complex climate issues. By examining an extensive dataset of visual posts collected from five organization accounts on two multimodal social media platforms, Twitter and Instagram, we conducted a cross-platform comparison of visual content categories and visual features related to climate change. Through deep-learning-based unsupervised image clustering, we discovered that visual content on both platforms could be broadly classified into five categories: infographics/captioned images, nature landscape/wildlife, climate activism, technology, and data visualization. However, these categories were not equally represented on each platform. Instagram featured more nature landscape/wildlife content, while Twitter showed more infographics/captioned images and data visualization. Through computational visual analysis, we found that the two platforms also presented significant differences in overall warm and cool colors, brightness, colorfulness, visual complexity, and presence of faces. Additionally, we identified platform-specific patterns of engagement associated with these categories and features. With the urgency to address climate change, these findings can guide climate advocacy organizations in developing strategies tailored to each platform's specific characteristics for maximum effectiveness. This study highlights the significance of using computational methods in efficiently uncovering meaningful themes from extensive visual data and quantifying aesthetic features in strategic communication.

1. Introduction

Social media have become powerful channels for advocacy organizations to effectively communicate with key stakeholders, offering a direct avenue for engagement with their audience and cultivating meaningful relationships (Men & Tsai, 2015; Wang & Yang, 2020). In particular, recent work has highlighted the effectiveness of advocacy organizations' use of social media for communicating **climate change** issues (Lee, VanDyke, & Cummins, 2018; Center, 2014), which is an ongoing challenge facing the global community (IPCC, 2022). At the same time, multimodal social media platforms like Instagram and Twitter have prompted new strategies that prioritize the creation and promotion of **visuals** to deliver key content. Visuals were ubiquitously used when illustrating the impacts of climate change and potential mitigations (Chapman, Corner, Webster, & Markowitz, 2016). While there has been established research on the use of social media for communicating climate change, there is a lack of understanding of how climate advocacy organizations strategically use climate change related visuals to engage audiences on social media.

An increasingly important measure of advocacy organizations' efficacy is their degree of social media engagement. Engagement metrics such as likes, comments, and shares not only provide direct and real-

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time insights into the organization's outreach, agenda-setting, and mobilization potential but also serve as reliable proxies for traditional performance indicators, such as an organization's charitable donations (Lee, 2021). Social media engagement is especially important for climate change advocacy because such issues tend to be complex, controversial, geographically distant, and often lack an immediate impact on audiences' surroundings (Sinatra & Seyranian, 2015).

Visuals, as powerful means for conveying complex concepts, can boost engagement and raise awareness of climate change. The effectiveness of visuals is well documented in concepts such as the indexicality of visuals, which posits that visuals provide a true-to-life representation of information (Messaris & Abraham, 2001). Compared to single-modality text, visuals are more attention-grabbing (Galloway, 2017) and evoke stronger emotional responses (Iyer, Webster, Hornsey, & Vanman, 2014). By simplifying abstract ideas and making them more tangible, visuals have the capability to enhance public understanding of intricate scientific issues like climate change (Schäfer, 2020). Moreover, visual content plays a crucial role in shaping public perceptions and attitudes towards climate change, exerting a profound influence on individual and collective actions (O'Neill, 2013; O'Neill & Nicholson-Cole, 2009).

In our study, we examine the nuances of climate change visuals and their engagement on Twitter and Instagram. We chose Instagram and Twitter for our analysis given their critical roles in the dissemination of information. As reported by Pew Research Center (2023), 16% and 12% of U.S. adults, respectively, regularly get news from these platforms. These platforms are not only prevalent in advocacy communication and online mobilizations (Lu & Peng, 2024; Molder, Lakind, Clemmons, & Chen, 2022), but are also favored by climate advocacy organizations for their audience reach (Molder et al., 2022). Furthermore, both platforms allow users to integrate visuals in their posts, providing an opportunity to compare the role of visuals in eliciting audience engagement.

However, the unique cultural norms and features of each platform, such as user demographics, content focus, and visual aesthetics, may result in varied engagement patterns, thereby influencing the tailored strategies organizations employ to effectively communicate the issue and optimize engagement (Niederer, 2018). At the same time, organizations may also seek platform convergence, aiming to maintain a consistent image and deliver uniform messages to audiences across platforms. Existing studies on climate change visuals mostly focus on a single platform, potentially yielding an incomplete understanding of the broader impact of climate change visuals in the digital realm. Our study addresses this gap by adopting a cross-platform analysis, examining the degree of divergence and convergence in climate change visuals circulated on social media. This approach offers a more comprehensive perspective, acknowledging and exploring the multifaceted nature of social media engagement with this critical issue (Pressgrove, Janoske, & Haught, 2018).

Using computational visual analysis on 4517 images posted by five organizational accounts, the current study compares the visual content categories and features of climate change visuals on Twitter and Instagram, and explores how these categories and features are associated with social media engagement. We derived visual content categories through unsupervised image clustering (Lu & Peng, 2024; Zhang and Peng, 2021) and we extracted a broad range of visual features, such as color features, visual complexity, and faces, through computer vision approaches (Lu & Pan, 2022; Sharma & Peng, 2023). We then compared the use of these visual content categories and features across platforms and investigated how they predict social media engagement (post likes, comments, and retweets). By analyzing the factors that influence the popularity of climate change images on social media, the study aims to identify strategies that raise engagement with this issue. The findings of the study offer insights for public relations practitioners and climate advocacy organizations seeking to enhance the visibility of their content, interact meaningfully with their audience, and adjust their approaches to suit the distinct characteristics of each platform. Methodologically, we present how computational visual analysis and deep-learning-based frameworks can be extended to the intersection between public relations research and visual communication.

2. Literature review

2.1. Climate advocacy organizations: using social media for engagement

Advocacy organizations have increasingly turned to social media platforms as powerful tools to address and promote various issues, engage with the public, mobilize support, and drive changes (Men & Tsai, 2015). The true impact of their content, frequently assessed through the lens of engagement, is a central focus in public relations research. Engagement on social media platforms has been interpreted from cognitive, emotional, behavioral, and social aspects (Dhanesh, 2017; Smith & Gallicano, 2015). This paper aligns with the dominant interpretation of social media engagement, emphasizing the communicative interactions between advocacy organizations and the public, quantified by likes, comments, and retweets (Bonsón & Ratkai, 2013; Chon & Kim, 2022; Ji, Chen, Tao, & Li, 2019).

Social media engagement has been recognized for its importance on organizational outcomes. Engagement provides direct and real-time insights of the level of outreach and agenda-setting as well as the potential for further mobilization and public policy changes. On social media, content with higher engagement metrics is more likely to be amplified by algorithms, which can result in a broader audience reach and a wider community engagement. At the same time, social media engagement is also a reliable proxy of traditional performance indicators, such as an organization's charitable donations (Lee, 2021) and organization-public relationship (Men & Tsai, 2014). For example, social media engagement with the government can also enhance government branding (Sevin, 2016), attract resources (Cleave, Arku, & Chatwin, 2017), and aid in crisis management (Chon & Kim, 2022). Thus, a comprehensive understanding of how social media strategies that advocacy organizations apply influence social media engagement not only deepens our knowledge in the field but also offers practical insights for organizations aiming to maximize these positive outcomes.

Among various advocacy organizations, the advocacy for climate change presents an exemplary case study to understand how strategic content creation on these platforms can significantly amplify the message of environmental advocacy organizations, and raise awareness and drive action on this pressing global issue through enhanced social media engagement. During significant climate events like the Paris climate talks (COP21), climate advocates can craft highly-engaging social media content using visuals to demonstrate the unity and commitment of global leaders in addressing climate change (Hopke & Hestres, 2018). Given the complexity and controversy surrounding climate change (Sinatra & Seyranian, 2015), increasing engagement in climate advocacy may enhance the likelihood of algorithms amplifying such content compared to other topics, thereby reaching a broader audience or community. For example, younger demographics, who are avid users of social media, can be mobilized by climate advocacy content to become a new generation of climate change activists. With this expanded audience base and mobilization groups, advocacy messages can gain more legitimacy and have a more extensive impact on public policy (Böhler, Hanegraaff, & Schulze, 2022). Furthermore, as climate change discussions become increasingly fragmented due to the involvement of various communicators (Canon, Boyle, & Hepworth, 2022; Moser, 2010), higher engagement with advocacy content may increase the chances of the general audience aligning with the advocacy stance rather than encountering disinformation or denial (Krishna, 2021; McKie & Galloway, 2007).

2.2. Climate change advocacy through social media visuals

The strategic use of visual content has become increasingly common by climate advocacy organizations. Visuals can convey complex information in an easily digestible manner and are often more persuasive and emotionally evocative than text alone (Messaris, 1997). According to dual-coding theory, visual information undergoes distinct processing compared to verbal or textual information (Clark & Paivio, 1991). Visual information's perceptual features closely resemble the events they represent. This similarity facilitates more thorough information processing and quicker memory recall. It allows visuals to evoke a sense of immediacy and directness, enabling audiences to grasp the scale and severity of climate change more effectively than through text alone (O'Neill, 2017). For instance, visualization makes complex climate data accessible and understandable to a wide audience (Harold, Lorenzoni, Shipley, & Coventry, 2016). Visuals also possess the power to elicit emotions, which can influence perceptions, attitudes, and behaviors (Nabi, 2003). Images depicting the devastating impacts of climate change can arouse emotions such as fear, anger, or sadness, while images portraying mitigation and adaptation efforts can evoke hope and empowerment (O'Neill, Boykoff, Niemeyer, & Day, 2013; Hart & Feldman, 2016).

In understanding the relationship between social media visuals and engagement, existing studies underscore the multimedia essence of online posts integrating visuals, explaining their associations with engagement through mechanisms of media richness (Chen et al., 2020), vividness (Ji et al., 2019), and playfulness (McShane, Pancer, Poole, & Deng, 2021). Argyris, Wang, Kim, and Yin (2020) delve into the visual congruence between influencers and their followers, examining its correlation with social media engagement. In the context of climate change advocacy on social media, recent studies explored the use of types of images (e.g., images with identifiable people, protests) and visual frames (e.g., nation-state contributions, climate justice) through content analysis (Hopke & Hestres, 2018; León, Negredo, & Erviti, 2022). Studies (e.g., León et al., 2022) also find that visual features like presence of people can predict more social media engagement. However, implications of these studies are limited by singular climate events, short time frames for analysis, and subjective feature selection. A more systematic and granular approach is needed to examine different features of climate change visuals and how they predict social media engagement. To address this gap, our study examines climate visuals over extended time periods and analyzes a series of visual features. We seek to provide deeper insights into the intricate dynamics between climate change visuals and social media engagement.

2.3. Platform Divergence and Convergence in Climate Advocacy

While the wide array of social media platforms allows climate advocacy organizations to connect with diverse audiences, it also demands additional resources for managing their presence and adapting their messages across various channels. In this context, we examine two social media platforms —Instagram and Twitter—to evaluate their similarities and differences in advocacy strategies. We define *platform divergence* as the practice wherein advocacy organizations tailor unique messages to the distinct social and technological attributes of each social media platform, while *platform convergence* as the practice where advocacy groups use uniform messaging to ensure consistency across various social media platforms, despite their unique social and technological features (Bossetta and Schmøkel, 2022).

Adopting a platform divergence approach may be important for advocacy success as each social media platform has its own mode of presentation, range of affordances, and specific needs and tastes of the audience (Bossetta & Schmøkel, 2022; Gibbs, Meese, Arnold, Nansen, & Carter, 2015). We summarize some major differences between Twitter and Instagram, along the dimension of supported media, user demographics, content focus, visual aesthetics, and engagement (Table 1). For instance, Instagram is predominantly a visual-centric platform, while text precedes the presentation of visual content on Twitter. Twitter is often perceived as a platform rife with negativity and political

Table 1
A comparison between Instagram and Twitter.

	Instagram	Twitter	References
Supported media	Supports a combination of text, image, and videos. Does not support text-only posts. Emphasizes visuals first, accompanied by captions.	Supports a combination of text, image, and video. Text precedes the presentation of visual content.	Bossetta, 2018
User demographics	Predominantly younger audience under 30, focusing on lifestyle and personal expression	Diverse, often politically engaged	Auxier & Anderson, 2021;McClain, Widjaya, Rivero, & Smith, 2021;Schaeffer, 2021,
Content focus	Emphasizes the presentations of social relationship, self-presentation (i.e., selfies) and positive presentations (e.g., lifestyle and travel). More oriented towards expression of positive emotions	Oriented toward the discussion of public affairs, politics, and real-time information exchange. More acceptable of the expression of negative emotions	Bossetta & Schmøkel, 2022;Peng, 2021;Manikonda et al., 2016
Visual aesthetics	Emphasizes visually appealing content with a reputation for using aesthetically pleasing filters	Informal and spontaneous, complements and enhances tweets	Manovich, 2016;Pearce et al., 2020;Peng, 2017
Engagement	Likes, comments	Likes, comments, retweets	

tension, in contrast to Instagram which tends to emphasize positive self-expression and fostering social ties rather than fostering division (Manikonda, Meduri, & Kambhampati, 2016). Additionally, technological affordances of different platforms and how people perceive their functionalities also shape communication dynamics (Kreiss, Lawrence, & McGregor, 2018). Content creators may thus adopt strategies for different platforms, as supported by recent studies on popular climate change visuals. These studies found that climate change-related visuals on Instagram features visually-appealing natural landscapes predominantly (Pearce et al., 2020; Rogers, 2021), while those on Twitter combine visuals, text, scientific charts, and figures, occasionally advocating for controversial positions (Mooseder, Brantner, Zamith, & Pfeffer, 2023). In other words, specific content categories of climate change visuals may differ across social media platforms.

Meanwhile, platform convergence can occur for various reasons. Content creators, often constrained by limited resources and time, may recycle content across multiple platforms instead of tailoring content to different platforms. Advocacy groups seeking a consistent brand image may opt for standardized presence that resonates similarly with audiences across platforms. Empirical research suggests that both platform convergence and divergence can coexist, with the extent varying across contexts (Bossetta & Schmøkel, 2022; Farkas & Bene, 2021). In political campaigns, a large portion of the posts from politicians' accounts are identical between Facebook and Instagram, suggesting platform convergence (Bossetta & Schmøkel, 2022; Farkas & Bene, 2021). However, there is a lack of direct evidence regarding whether climate visuals converge in categories across social media platforms. Therefore, we propose our first two research questions:

RQ1: What visual content categories are present in climate change communications on Twitter and Instagram?

RQ2: How do these visual content categories converge or diverge on Twitter and Instagram?

In addition to content production, it is also critical to consider whether audience engagement with these visual content categories would vary across different platforms. Analyzing cross-platform audience engagement can uncover the types of content that gain popularity and reveal platform-specific cultural tastes and norms. Such knowledge would guide climate advocacy organizations in determining the most effective categories and strategies tailored to each platform for enhancing the visibility and engagement of their content. Indeed, prior research has shown that audiences from different platforms may respond distinctively to the same content attributes. For example, in political campaigns, Instagram users engage more with posts where politicians exhibit happiness, while Facebook users prefer those with calm expressions, suggesting that Instagram users may have a stronger preference for emotionally expressive content (Bossetta & Schmøkel, 2022). In our study, we explore whether Instagram and Twitter users exhibit different engagement patterns with climate change visuals content across platforms. Therefore, we propose our next research question:

RQ3: What visual content categories are associated with engagement on Twitter and Instagram, respectively?

2.4. Visual features and engagement across platforms

To maximize the attention and impact of climate change visuals on social media, advocacy organizations need to consider not only visual categories but also how an image is composed, determined by structural visual features such as pixel-level color characteristics or the presence of faces. We include two types of visual features for their theoretical importance in engagement. First, we consider low-level features, which encompass basic attributes such as color and edges. Low-level features can influence processing fluency and lead to different psychological reactions (e.g., arousal), subsequently contributing to varying levels of engagement with the content (Labrecque & Milne, 2012; Reber, Schwarz, & Winkielman, 2004). We also incorporate high-level features that represent more complex semantic concepts, such as objects and faces, as they are essential for strategies like storytelling to foster social media engagement (León et al., 2022).

Features from both levels are important for audience engagement. According to the Elaboration Likelihood Model (ELM), recipients rely on heuristic cues to form their perceptions about an issue under low elaboration (Petty & Cacioppo, 1986). Thus, climate advocacy organizations can strategically incorporate attention-eliciting low-level features to manipulate these cues to increase social media engagement, such as creating images with higher color complexity (Kanuri, Hughes, & Hodges, 2023). In addition to this peripheral route, the strategic use of these features can encourage recipients to pay more attention to the post and transition to the central route for more in-depth engagement with the content.

Research also argues that low-level features and high-level features involve different psychological processes. The Feature Integration Theory (FIT) posits that individual features like color and shape are registered early and automatically in visual processing before integrated into object characterization (Treisman & Gelade, 1980). Rouw, Kosslyn, and Hamel (1997) found that high-level features are more easily extracted from mental images than low-level features like line continuation. Thus, it is theoretically significant to compare low-level and high-level visual features and their association with content engagement.

While visual features play a crucial role in engagement, few studies have investigated how their strategic use and their potential to attract engagement differ across various social media platforms. In the climate change context, low-level visual features can predict naturalness perception in environmental scenes (Berman et al., 2014), and high-level human-related features are associated with social media engagement (León et al., 2022). However, most of these studies focus on a single platform. Therefore, we investigate the following visual features from a cross-platform perspective.

2.4.1. Warm and Cool Colors

The color feature is extensively researched in information science, psychology, and communication research (Huang, Kumar, Mitra, Zhu, & Zabih, 1999; Lu & Pan, 2022; Lu & Shen, 2023; Patiño-Escarcina & Costa, 2008; Wen, Peng, & Yang, 2023). Empirical studies have shown that different colors may be influencing visual engagement differently. In particular, *warm colors*, such as reds, yellows, and oranges, are associated with higher content engagement on social media (Peng & Jemmott, 2018; Sharma & Peng, 2023). In the context of climate change, as red symbolizes urgency and yellow or orange may indicate planetary warming, we expect that the use of warm colors can also elicit more engagement of social media posts.

In comparison, *cool colors*, such as greens and blues, are less arousing and less associated with higher social media engagement. However, in the context of climate change, these cool colors usually represent the Earth and the environment, commonly used in logos and branding for environmental organizations and campaigns. Thus, we expect that using these colors can also elicit reflective thoughts on Earth protection, ultimately reflected by more social media engagement. As Twitter and Instagram indicate different levels of negativity and visual appeals, climate change visuals may exhibit different use of colors in these two platforms.

2.4.2. Brightness and colorfulness

Besides particular colors, other pixel-level color features can also influence engagement with online content. We include *brightness*, a fundamental color feature that has shown mixed results with social media engagement in studies on social media visuals. For example, Sharma and Peng (2023) found that lower brightness predicts food image popularity, while Lu and Shen (2023) found that fact-checking videos with higher brightness gain more comments and reshares. It remains unclear whether brightness predicts climate change-related social media engagement. Meanwhile, prior research has also found that *colorfulness*, which describes color intensity, negatively predicts engagement on social media (Sharma & Peng, 2023). However, it is also worth examining if this association holds in the climate change context across platforms.

2.4.3. Visual complexity

Visual complexity, reflecting the degree of variety in visual stimuli (Pieters, Wedel, & Batra, 2010), can also influence social media engagement through impacting psychological consequences like attention and affective reactions (Pieters et al., 2010; Tuch et al., 2011). This study utilized a framework developed by Peng and Jemmott (2018) that consists of three dimensions of visual complexity: *feature complexity* pertaining to the level of detail and richness in the visual elements; *compositional complexity* measuring the clustering or spread of visual elements through distribution; *color variety* representing the range of colors present in the image. These different complexity indicators predict psychological outcomes in different ways. For example, Pieters et al. (2010) found higher feature complexity negatively impacts on both brand attention and attitude toward the advertisement. Sharma and Peng (2023) found feature complexity predicts higher post engagement on social media, while compositional complexity predicts in a reverse way. This could potentially be explained through the construal level theory, which suggests that less abstract visuals are perceived as psychologically 'closer' to the individual, and consequently leading to stronger intentions to engage in climate change mitigation behaviors (Duan, Zwickle, & Takahashi, 2022). However, there are no conclusive results regarding these complexity dimensions across platforms and we examine how they predict climate post engagement across Twitter and Instagram.

2.4.4. Faces

We also examine the presence of *human faces* in climate-related images, as they affect image perceptions and content engagement (Joo, Li, Steen, & Zhu, 2014; Joo, Steen, & Zhu, 2015; Li & Xie, 2020; Peng, 2018). The presence of faces on social media has been found to predict higher audience engagement (Bakhshi, Shamma, & Gilbert, 2014; Li & Xie, 2020). Instagram posts featuring faces, across demographic groups, tend to attract more likes and comments than posts with no faces (Bakhshi, Shamma, & Gilbert, 2014). In the context of climate change, images that depict non-staged "real people" with emotions predict more post engagements (León et al., 2022).

While the effects of face presence social media engagement is well documented, the comparison between a single face and multiple faces is less clear. Similar to how group-depiction visuals can predict online engagement of political protests (Valenzuela, Piña, & Ramírez, 2017), featuring a group of people in climate change visuals may convey a sense of solidarity and empowerment, leading to higher social media engagement. However, in one empirical analysis of Instagram photos, whether a post features a group photo or a single person's photo does not substantially predict likes and comments of the post (Bakhshi, Shamma, & Gilbert, 2014). Therefore, we also include the comparison between single face and multiple face in our cross-platform investigation.

Based on the above discussion, we propose the following research questions examining the presentation of visual features and their relationship with social media engagement:

RQ4: Do visual features of climate change diverge or converge on Twitter and Instagram?

RQ5: What visual features are associated with more engagement on Twitter and Instagram respectively?

3. Method

3.1. Data collection

We approached these questions by establishing a representative sample of climate change visual posts on Twitter and Instagram, which is part of a broader initiative to collect social media posts with diverse topics (more details in Supplemental Material I). The data collection includes two steps: 1) identifying popular related hashtags and 2) selecting key accounts and downloading their posts.

Seed hashtag selection. We compiled a list of hashtags for the topic of climate change through literature search and ranked their popularity on Twitter and Instagram respectively. Since these hashtags show different attitudinal stances, we divided the hashtags into three categories (i.e., climate change advocate, climate change denial, and neutral) and kept the top 5 most popular hashtags from each category. Table 2 presents hashtags selected for this step on Twitter and Instagram.

Account selection. We first identified the top 20 accounts that appear on both platforms and attract the most engagement during this time period, measured by the total number of likes received on their posts. Posts from these accounts act as examples of highly engaging content, enabling us to examine specific visual elements that connect effectively with the audience. Using the combined set of these hashtags as data collection keywords, we downloaded all posts with images from these users using Twitter Academic API and 4 K Stogram[4] with a time frame from January 2018 to April 2022.

To ensure a meaningful comparison, we only retained accounts that had over 50 image posts on both platforms. As Table 3 shows, five accounts met this criterion and were included in the analyses: United Nations Environment Programme (UNEP), World Wide Fund (WWF), World Economic Forum (WEF), Greenpeace, and Extinction Rebellion. In total, we included 4517 images from these five organizational accounts in our analysis, after removing missing data.

3.2. Measures

Visual Content Categories. To categorize climate change related images into different visual content categories, we utilized deep-learning-based unsupervised image clustering (Zhang and Peng, 2021). In the first step, we applied a transfer learning approach involving a pre-trained VGG16-hybrid1365 model to extract features from the images (Zhou, Lapedriza, Khosla, Oliva, & Torralba, 2017). The VGG16-hybrid1365 model was trained on a combination of the ImageNet Large Scale Visual Recognition Challenge and Places365-Standard datasets, and we applied this model to extract visual patterns from each image. This results in a 4,096-dimensional feature vector for each

Table 2
Top 15 seed hashtags of climate change on Instagram and Twitter for identifying key accounts.

	Top 15 Instagram Hashtags by Popularity	Top 15 Twitter Hashtags by Popularity
Climate change advocate	#ClimateCrisis, #WorldEnvironmentDay, #SaveWater, #WaterConservation, #IPCC	#ClimateCrisis, #WorldEnvironmentDay, #ParisAgreement, #IPCC, #SaveWater
Climate change denial	#ClimateChangeHoax, #ClimateHoax, #GlobalWarmingHoax, #ClimateFraud, #ClimateScam	#ClimateHoax, #ClimateCult, #ClimateScam, #ClimateFraud, #ClimateHysteria
Neutral	#ClimateChange, #Monsoon, #GlobalWarming, #Heatwave, #ClimateEmergency	#ClimateChange, #ClimateEmergency, #Cowx, #GlobalWarming, #Heatwave

[4] 4 K Stogram is a software application that allows users to download content from public accounts, hashtags, and locations.

Table 3
Climate Advocacy Organization Accounts Selected.

Organization Name	Instagram Handle	Twitter Handle
United Nations Environment Programme (UNEP)	@unep	@UNEP
World Wide Fund (WWF)	@wwf	@World_Wildlife
World Economic Forum (WEF)	@worldeconomicforum	@wef
Greenpeace	@greenpeace	@greenpeace
Extinction Rebellion	@extinctionrebellion	@ExtinctionR

image.

We then used unsupervised *K*-means clustering to group the feature arrays by testing different Ks (K = 10, 15, 20). For each *K*-cluster solution, we inspected 20 random images from each cluster to assess whether they formed a coherent category. We went through a two-step process for this validation. First, we coded all pictures in K= 20 cluster and identified five categories that exhibited internal coherence and distinctiveness, 1) climate activism, 2) nature landscape/wildlife, 3) technology, 4) data visualization, and 5) infographics (see detailed explanation of each category in the results section). We then re-labeled images of each cluster in each *K*-cluster solution into these five categories. To validate the optimal K for the clustering algorithm, we determined the accuracy of each *K*-cluster solution by calculating within-cluster consistency, which is the proportion of images out of 20 that fell into one majority category. Ultimately, we adopted the 15-cluster solution, which demonstrated a highest within-cluster consistency ranging from 75% to 100%. More details are provided in Supplementary Material II.

For structural visual features, we used the Athec Python package developed by Peng (2022) and we outlined the computation of each feature as below.

Warm and cool colors. We categorized the colors used in each image by matching the RGB channels of each pixel to 11 basic color categories. We then calculated the percentages of five colors, including three warm colors (i.e., red, orange, and yellow) and two cool colors (i.e., green and blue), in each image to represent the presence of warm and cool colors.

Brightness. We converted the image into the HSV color space and averaged the V (Value) across all pixels to represent image brightness.

Colorfulness. Colorfulness was measured using a formula developed by Hasler and Suesstrunk (2003), which was designed to align with human perceptions of colorfulness.

Feature complexity. We used edge density to denote feature complexity. The edges were detected with the Canny method, which identifies pixel points where there are sudden changes in image properties like color or brightness. Such changes usually indicate the contours or texture of objects. An image with numerous objects and details will have more edges, and hence the area proportion filled with edge points can be used to measure feature complexity (Peng & Jemmott, 2018).

Compositional complexity. Following Peng and Jemmott (2018), we used edge distance to denote compositional complexity. In an image with high compositional complexity, edge points should be further away from each other. We calculated the average Euclidean distance among all the pairs of edge points, divided by the image's diagonal length.

Color variety. We used the hue count formula (Ke, Tang, & Jing, 2006) in the Athec package. This method involved converting the image to the HSV color space and retaining perceptually colorful pixels based on specific criteria ($S > 0.2$, $0.15 < V < 0.85$). The image was then divided into 20 hue spectrum bins, and pixels were assigned to the corresponding bins. The algorithm counted the number of bins that met a particular threshold based on the number of pixels in each bin.

Faces. To detect faces in the images, we employed the Face+ + API.[5] The API identified the number of faces and provided information of these faces such as their location and gaze. We created a categorical variable comprising three levels: images with no faces, images with one face, and images displaying multiple faces to denote both the presence and the number of faces.

3.3. Analytical Strategy

To answer RQ1, we used deep-learning-based image clustering to extract visual content categories, as detailed above. Then we conducted a chi-square test to examine the differences in visual content categories between the two platforms to answer RQ2.

For the associations between visual post characteristics and social media engagement across platforms (RQ3 and RQ5), we operationalized engagement as the number of likes and comments on Instagram, and the number of likes, comments, and retweets on Twitter for each visual post. A series of multilevel regression analyses were used to model the relationship between different characteristics and engagement using an R package lme4. The models treated accounts (N = 5) as random effects. Content categories and visual features including warm and cool colors, brightness and colorfulness, visual complexity, and faces were included as fixed effects. The number of followers (log transformed) of each account was included as a control variable. Due to the highly skewed distribution of the engagement variables (e.g., number of likes), a natural log transformation was applied to these dependent variables to improve normality.

To answer the cross-platform question on visual features (RQ4), we first employed *t*-tests and chi-square tests to compare visual features across Twitter and Instagram using the full sample, and then conducted the same tests within each of the five visual content categories between the two platforms. Given that visual content categories were correlated with visual features (see correlation in Table S1 in Supplemental Material), comparisons within each subcategory serve as a robustness test. Multiple comparisons were addressed by applying the Bonferroni correction method. Specifically, the p-values were multiplied by the number of tests performed.

4. Results

4.1. Five main visual content categories

RQ1 asks the visual content categories posted by climate change advocacy organizations on social media. We extracted five broad categories of climate change visuals. The first category, *infographics/captioned images*, includes images that utilize posters, infographics, or overlaid text to present statistics, facts, and figures related to climate change. Cartoons, memes, quotes, and screenshot of tweets are also included in this category. The second category, *nature landscape/wildlife*, encompasses photographs that showcase the beauty of natural landscapes, including forests, oceans, mountains, and other scenic views. It also includes wildlife photography capturing various animal species and their habitats. The third category, *climate activism*, features climate strikes, protests, demonstrations, and other forms of activism aimed at raising awareness and demanding action on climate change. These visuals prominently showcase the faces of people, including protestors, speakers, politicians, and individuals. The fourth category, *technology*, includes images that promote renewable energy technologies such as wind farms, solar panels, hydropower, and sustainable transportation options like airplanes, bicycles, and electric cars. The last category, *data visualization*, focuses on representing numerical or quantitative data through charts, graphs, and maps. It utilizes data visualizations to present information and trends related to climate change impacts, causes,

[5] https://www.faceplusplus.com/

and solutions.

4.2. Divergence and convergence of visual content categories

RQ2 asks whether visual content categories of climate change diverge or converge on Twitter and Instagram. Fig. 1 presents the frequency distribution of the five categories on each platform. While "nature landscape/wildlife" (36.1%) is the most popular on Instagram, "infographics" (40.1%) is the most prominent on Twitter. The chi-squared test revealed that the distribution of categories differs significantly between Instagram and Twitter ($\chi^2 = 388.98$, df $= 4$, $p < .001$). Post-hoc analyses of pairwise comparison of proportions reveal that Twitter had significantly more infographics/captioned images and data visualization than Instagram ($p < .001$ for both tests), while Instagram had more images about nature landscape/wildlife ($p < .001$) and technology ($p = .001$). The distribution of climate activism visuals did not differ between the two platforms. Fig. 2 shows example images from each category on the two platforms.

4.3. Visual content categories and social media engagement across platforms

RQ3 examines the association between visual content categories and social media engagement on each platform, with detailed results presented in Table 4. Images that depict nature landscapes/wildlife are associated with a significantly higher number of likes ($B = 0.310$, $p < .001$) compared to infographics/captioned images on Instagram. Additionally, technology-focused images are associated with a higher number of likes on Instagram ($B = 0.153$, $p = .039$) but a reduced number of retweets on Twitter ($B = -0.136$, $p = .027$). Climate activism images are associated with a significantly higher number of likes on Instagram ($B = 0.195$, $p = .010$), but a reduced number of comments ($B = -0.168$, $p = .013$) and retweets ($B = -0.231$, $p < .001$) on Twitter, compared to the same reference group. Data visualization images are linked to a significantly lower number of likes ($B = -0.157$, $p = .006$) and retweets on Twitter ($B = -0.122$, $p = .036$). Comparison between other categories did not reveal any significant differences.

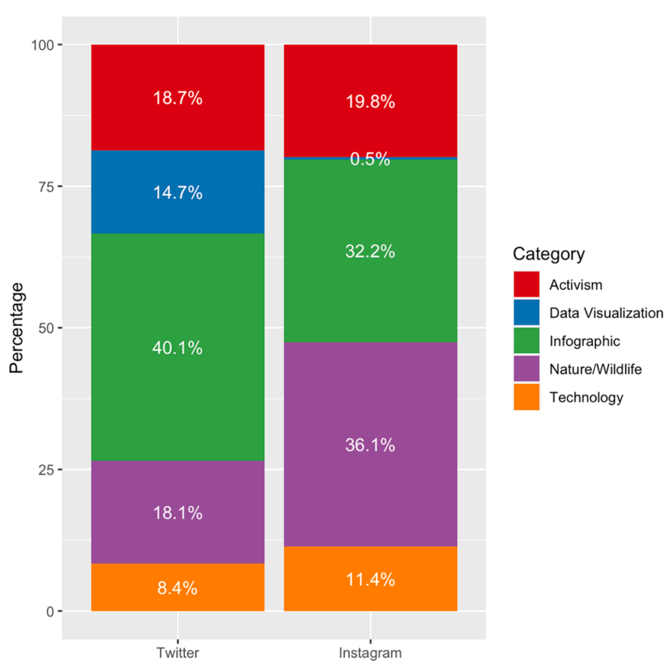

Fig. 1. Frequency distribution of five categories on Instagram and Twitter.

4.4. Divergence and convergence of visual features

To examine divergence and convergence of visual features between Instagram and Twitter (RQ4), we compared visual features between the two platforms using Welch's *t*-tests and chi-square tests. Table 5 displays the results of the *t*-tests conducted on the full sample and within each subcategory. We found that visual features of images posted on Twitter and Instagram differ in terms of warm and cool colors, brightness and colorfulness, visual complexity, and face category.

In terms of specific colors, images posted on Instagram tended to feature a higher proportion of green ($M = 0.125$, $t = 5.057$, $p < .001$), blue ($M = 0.182$, $t = 3.736$, $p = .002$), orange ($M = 0.036$, $t = 3.588$, $p = .003$), and yellow ($M = 0.043$, $t = 3.356$, $p = .008$) colors compared to Twitter images, with mean values of 0.096, 0.154, 0.025, and 0.033, respectively. However, there was no significant difference in the mean values for red between Twitter and Instagram. The subcategory analyses indicated that within each visual content category, the specific colors did not show significant differences. This suggests that the variations in color observed in the full sample are more likely to be influenced by the distribution of visual content categories on the two platforms.

Twitter images had a significantly higher mean for brightness ($M = 166.629$) compared to Instagram images ($M = 142.984$; $t = -15.48$, $p < .001$). Conversely, Instagram images had a significantly higher mean for colorfulness ($M = 51.352$) compared to Twitter images ($M = 47.639$; $t = 4.08$, $p < .001$). Therefore, we can conclude that images posted on Twitter were generally brighter, while images posted on Instagram were generally more colorful. Within each visual content category, there was no significant difference of colorfulness between Instagram and Twitter. The differences between brightness were also not significant for most of the visual content categories, except for infographics/captioned images. Consistent with results from the full sample analysis, infographics/captioned images tended to be brighter on Twitter than those on Instagram ($t = -5.867$, $p < .001$).

In regards to visual complexity, edge density was significantly lower in Twitter images ($M = 0.096$) compared to Instagram images ($M = 0.107$; $t = 6.761$, $p < .001$), suggesting that Instagram images are richer and include more perceptual details. However, edge distance was significantly higher in Twitter images ($M = 0.323$) compared to Instagram images ($M = 0.319$; $t = -3.483$, $p = .005$). It shows that images on Twitter had a more dispersed composition than those on Instagram, which tend to be clustered around one specific area. There was no significant difference in color variety between Twitter and Instagram images. Subcategory analyses showed that edge density and color variety did not differ between platforms in all visual categories. The disparity in edge density persisted within infographics/captioned images, revealing that infographics/captioned images on Twitter tended to have fewer details compared to those on Instagram ($t = 5.350$, $p < .001$).

Finally, while the majority of the images on Twitter and Instagram do not feature faces (89.8% and 86.8% respectively), Instagram tends to have a higher frequency of images with one (9.3%) or multiple faces (3.9%) compared to Twitter (7.6% for one face and 2.6% for multiple faces). The chi-squared test revealed a significant association between the presence of faces and the platforms ($\chi^2 = 10.128$, df $= 2$, $p = .006$). This indicates that the distribution of the face differs significantly between Instagram and Twitter. We further conducted chi-square tests within each visual category and found that face was also associated with the platforms in the climate activism categories. More specifically, images showed more faces on Instagram than on Twitter ($\chi^2 = 11.851$, df $=$ 2, $p = .003$).

4.5. Visual features and Social Media Engagement

RQ5 concerns the visual features' association with engagement on both platforms. As shown in Table 4, in regard to the use of warm and cool colors, orange color was associated with a higher number of comments on Twitter ($B = 0.539$, $p = .031$), and the use of blue color had a

Fig. 2. Example images from the following categories: climate activism (row 1), infographics/captioned image (row 2), nature landscape/wildlife (row 3), technology (row 4), and data visualization (row 5).

positive effect on the number of likes ($B = 0.345$, $p < .001$) and retweets ($B = 0.218$, $p = .013$). Analysis in the visual content subcategories reveals that these effects were driven by images in captioned image/infographics category on Instagram and Twitter (see Table S2 in Supplementary Material). Brightness positively predicted the number of comments on Instagram ($B = 0.001$, $p = .044$), while colorfulness negatively predicted the number of likes on Instagram ($B = -0.003$, $p = .005$) and on Twitter ($B = -0.002$, $p = .021$).

As for visual complexity, compositional complexity was associated with a lower number of likes on Instagram ($B = -1.291$, $p = .030$), while the other two dimensions (i.e., feature complexity and color variety) did not have an effect on the number of likes and comments on Instagram. On Twitter, feature complexity had a positive effect on the number of likes ($B = 1.086$, $p = .008$) and retweets ($B = 0.884$, $p = .034$, while compositional complexity had a negative effect on the number of likes ($B = -1.171$, $p = .008$), comments ($B = -1.588$, $p = .002$), and retweets ($B = -0.973$, $p = .031$). It suggests that on Twitter, images with more details and are less spread out attracted more engagement. There was no significant effect of color variety on all engagement outcomes on Twitter. Lastly, images with one face were associated with a higher number of comments on Twitter ($B = 0.165$, $p = .030$). Images with multiple faces were found to have more liking compared to images with no face on Instagram ($B = 0.301$, $p = .012$) and on Twitter ($B = 0.210$, $p = .038$).

5. Discussion

Advocacy organizations are increasingly relying on multimodal social media platforms such as Instagram and Twitter to disseminate their messages and directly engage with their audience. While previous research has recognized the importance of social media engagement in driving organizational outcomes, there is a lack of comprehensive understanding of the specific visual strategies and tactics that can effectively enhance engagement on these platforms, particularly within the context of climate advocacy. This gap inhibits both theoretical advancements in the field of public relations and the practical implementation of strategies aimed at maximizing positive outcomes for advocacy organizations seeking to amplify their message and mobilize support for climate change through social media engagement. Analyzing a large dataset of image posts from two popular platforms, Twitter and Instagram, we compared and contrasted visual content categories and features of visual content from climate advocacy organization accounts, and investigated how these characteristics are associated with user engagement on each platform. Through deep-learning-based image

Table 4
Multilevel analyses predicting engagement on Instagram and Twitter.

	Instagram		Twitter		
Predictors	**Likes (log-trans.)** *Estimates*	**Comments (log-trans.)** *Estimates*	**Likes (log-trans.)** *Estimates*	**Comments (log-trans.)** *Estimates*	**Retweets (log-trans.)** *Estimates*
(Intercept)	3.314 * **	1.368*	1.329	-1.657	1.498
Followers (log)	0.424 * **	0.190 * **	0.242	0.257 *	0.183
Visual Categories (ref. = Captioned image/infographic)					
Nature/Wildlife	0.310 * **	-0.082	-0.069	-0.098	-0.089
Technology	0.153 *	-0.091	0.020	-0.042	-0.136 *
Activism	0.195 *	-0.074	-0.019	-0.168 *	-0.231 * **
Data Vis.	-0.321	-0.642	-0.157 * *	-0.038	-0.122 *
Warm and cool colors					
Red	0.209	0.296	0.013	-0.007	0.140
Orange	0.226	0.330	0.248	0.539 *	0.278
Yellow	-0.147	-0.384	0.165	-0.059	0.245
Green	-0.073	-0.135	0.168	-0.152	-0.008
Blue	0.059	-0.060	0.345 * **	0.186	0.218 *
Brightness	0.001	0.001 *	0.001	-0.00004	0.001
Colorful	-0.003 * *	-0.002	-0.002 *	-0.001	-0.001
Visual complexity					
Edge density	0.472	0.690	1.086 * *	0.791	0.884 *
Edge distance	-1.291 *	-0.218	-1.171 * *	-1.588 * *	-0.973 *
Color Variety	0.001	-0.003	0.009	0.0001	0.006
Face (ref. = No face)					
One Face	0.067	0.032	-0.035	0.165 *	-0.093
Multiple Face	0.301 *	0.017	0.210 *	0.137	0.158
Random Effects					
σ^2	0.70	0.93	0.66	0.86	0.68
τ_{00}	0.30 $_{account}$	0.30 $_{account}$	0.17 $_{account}$	0.03 $_{account}$	0.13 $_{account}$
ICC	0.30	0.25	0.21	0.04	0.16
N	5 $_{account}$	5 $_{account}$	5 $_{account}$	5 $_{account}$	5 $_{account}$
Observations	1655	1655	2862	2862	2862
Marginal R^2 / Conditional R^2	0.195 / 0.437	0.046 / 0.281	0.039 / 0.239	0.050 / 0.084	0.039 / 0.193

Note: * $p < .05$, * * $p < .01$, * ** $p < .001$.

Table 5
Results of *t*-tests comparing visual features between Instagram and Twitter.

Visual Features	Mean Difference (Instagram-Twitter)					
	All Sample	Infographics/Captioned images	Nature Landscape/Wildlife	Climate activism	Technology	Data visualization
Warm and cool colors						
Red	-0.0002	-0.006	0.004	0.004	0.007	0.004
Orange	0.011 * *	0.008	0.013	0.008	0.005	0.0004
Yellow	0.010 * *	0.015	0.010	0.009	-0.006	0.060
Green	0.030 * **	0.016	0.005	0.017	-0.016	0.080
Blue	0.027 * *	0.006	0.008	-0.015	0.011	0.162
Brightness	-23.645 * **	-16.849 * **	0.223	3.903	-3.235	-26.531
Colorfulness	3.713 * **	2.279	3.641	3.510	3.831	31.143
Visual complexity						
Edge density	0.012 * **	0.012 * **	-0.0003	-0.004	-0.004	0.018
Edge distance	-0.005 * *	-0.006	-0.003	0.004	-0.008	0.002
Color Variety	0.104	-0.117	-0.059	-0.266	-0.127	-0.590
N	4517	1681	1117	862	428	429

Note: * $p < .05$, * * $p < .01$, * ** $p < .001$. *p*-value was Bonferroni-corrected.

clustering, we found that visual content on both platforms fell into five categories broadly consistent with past research: infographics/captioned images, nature landscape/wildlife, climate activism, technology, and data visualization. Yet these categories were not equally represented on each platform, with nature landscape/wildlife more prevalent on Instagram while infographics/captioned images and data visualization more prevalent on Twitter. Furthermore, overall Twitter and Instagram visual content differ in warm and cool colors, brightness and colorfulness, feature and compositional complexity, and face presence, and most of these visual differences seem to stem from the divergent visual content on these platforms. Finally, we found both convergence and divergence with regard to visual content categories and features and engagement dynamics on both platforms.

5.1. *Same visual categories, different presence*

Our findings indicate that climate advocacy organizations disseminate content in five visual categories on both Instagram and Twitter. These categories align closely with a recent study examining climate change visuals on Twitter by Mooseder et al. (2023). This suggests a consistent portrayal of climate change content across platforms. However, a notable divergence arises in terms of content emphasis. These same advocacy accounts appeared to strategically select and emphasize specific visual content categories catering to each platform. Instagram posts feature predominantly photographs, particularly nature landscapes/wildlife imagery. In contrast, visual content on Twitter leans more heavily on data visualization and infographics. This observation is in line with prior research investigating visual representation patterns of climate change on both Twitter and Instagram, as highlighted by Pearce et al. (2020) and Rogers (2021). Note that these two prior studies retrieved visual content using the same hashtags or search terms, yet such content was likely produced by *different* organizational and individual accounts. By contrast, the current study compared content from the *same* advocacy accounts on both Instagram and Twitter. As such, our findings suggest that the content category divergence we observed may be derived from the strategic choices of climate advocacy organizations themselves, adapting their message to unique platform affordances and their perceived audience preferences. This conscious and strategic choice by advocacy organizations might in turn reinforce existing perception of platform cultures and perpetuate audience preferences (Altheide, 2004; Burgess & Matamoros-Fernández, 2016).

5.2. Divergence and convergence of visual features

In addition to visual content categories, our study is among the first to establish the coexistence of divergence and convergence of specific visual features, which can influence human perception and content engagement more fundamentally, in climate change visuals across platforms. We discovered significant differences between Twitter and Instagram in the majority of analyzed visual features. First, Instagram images exhibited a higher prevalence of warm (yellow and orange) and cool colors (green and blue), lower brightness, and were more colorful than their Twitter counterparts. Second, Instagram images tended to be more complex in features, showcasing a multitude of elements and details, but less complex in composition when compared to Twitter images. Lastly, the presence of faces differs between the platforms, with Instagram images having a higher frequency of images featuring faces compared to Twitter images. However, when comparing within each of the five visual content categories, the above differences dissipated with the exceptions of brightness and complexity within the visual category of captioned images/infographics, as well as in face presence within the category of climate activism. This implies that the observed overall divergence in visual features is more likely a result of the different proportion of content categories present on both platforms.

While our results may not conclusively establish direct evidence of the differences and similarities in platform affordances between Twitter and Instagram, they suggest that *perceptions* of platform affordances, cultures, and audiences might contribute to measurable divergence in visual content categories (and by extension, visual features). These differences, in turn, could potentially reinforce such perceptions. For example, Instagram's emphasis on visually captivating and aesthetically pleasing content (Manovich, 2016) may affect the color and composition of visuals on Instagram. Similarly, research shows that users prefer Instagram over Twitter for visual self-presentation (Steffan, 2020) and social interactions (Blight, Ruppel, & Schoenbauer, 2017), and crowds tend to dominate visuals about activism (Joo & Steinert-Threlkeld, 2022). Combined, they may explain the greater prevalence of faces on Instagram than Twitter, especially when depicting climate activism. Such perceptions of platform differences are self-reinforcing, as they further cultivate different audiences and their media consumption preferences across social media platforms, influencing advocacy organizations' strategic use and adaptation of their visual messages to accommodate the perceived divergence.

5.3. Audience engagement with climate change posts

Audience engagement of social media posts is a critical and measurable component of climate advocacy, because of social media's enormous potential to amplify the message, reach broader audiences, and mobilize public support for campaigns, protests and policy change. Collectively, our findings suggest that some visual features can be useful in fostering engagement, but their impact is context- and platform-dependent, which indicate that climate change advocacy organizations should adopt a measured and goal-oriented strategy to communicate on social media.

Specifically, on Instagram, posts featuring nature and wildlife content receive more likes compared to captioned images/infographics. This pattern suggests that photographs of natural landscapes may be aesthetically appealing and generate audience reactions such as likes. These findings align with previous observations regarding politicians' visual messages on Instagram, where images of landscape and architecture tend to generate more likes (Peng, 2021). Taken together, these patterns suggest that images of nature may serve as eye-candy in users' newsfeeds to attract likes.

Furthermore, the study reveals that captioned images/infographics, as the reference group in our regression analysis, are effective in engaging audiences on topics related to climate change compared with the other content categories on Twitter. These types of visual content likely attract more attention because they can concisely convey complex information, making it easier for viewers to understand and absorb the message (Corner et al., 2015). In contrast, other categories like images of people in climate protests, demonstrations, and speeches, or images featuring renewable energy technologies and sustainable transportation options, while visually appealing, may not provide the same level of immediate information or clarity. However, these content categories attract more likes on Instagram than infographics, which, again, stresses the importance of cross-platform analysis. Data visualizations, although informative, might require more cognitive effort to interpret, which could explain their relatively lower engagement compared to the more straightforward and informative captioned images or infographics.

The study also examines visual features such as color percentages and visual complexity. However, the results are less consistent with prior research. While warm, arousing colors are generally expected to be associated with better engagement and cool, relaxing colors with lower engagement (Bakhshi & Gilbert, 2015; Sharma & Peng, 2023), the study finds that only orange color is associated with more comments and blue color predicts higher engagement in terms of likes and retweets and on Twitter. Further investigation suggests that this pattern may still be driven by the varying presentations of infographics and captioned images. Therefore, future research exploring the effects of aesthetic features should take into consideration content categories.

A closer qualitative examination reveals that orange was frequently employed in visualizations such as heatmaps on Instagram and Twitter. In these instances, the color served to highlight areas of intensity, effectively drawing attention to critical aspects of the presented data. This practice aligns with the symbolic power attributed to the warm color in scientific visualizations related to climate change, as it is commonly used to convey notions of danger, urgency, and the severity of environmental issues (Schneider, 2014). Leveraging the established psychological associations with the color, we posit that this heightened intensity may have contributed to increased user engagement. In contrast, the use of blue, especially in infographics on Twitter, is often as a background color. This choice seems guided by blue's associations with the earth and ocean, along with its connotations of calmness and coldness. In climate change maps, blue is frequently used to depict more favorable scenarios, signaling hope (Schneider & Nocke, 2018). This potentially affects how users perceive and engage with the content.

5.4. Computational visual analysis in advancing public relations research

Our study highlights the role of computational visual analysis in public relations. The advancement of computer vision techniques is a boon for scholars focusing on visual media presentations and effects in public relations research. Deep-learning-based image clustering used in our study presents an unsupervised machine learning approach to help researchers uncover meaningful visual themes and categories from massive data. This is particularly beneficial as scholars can identify visual categories that are not predefined.

Finally, the adoption of computational aesthetics and computer vision tools like Face+ + goes beyond just content themes of images; it concerns both low-level and high-level features that are fundamental to the construction of images. These analyses enable the capture of visual attributes challenging for humans to code, such as the proportions of different colors, compositional complexity, and presence of faces. Together, our results demonstrate the advantages of computational visual analysis on a large scale, which, when combined with human interpretation and qualitative examination, greatly enriches our understanding of visual content presentations and effects. As visual content has become increasingly popular in strategic communication, ranging from organizational advocacy communications to the cultivating of brand personality on social media (Wen et al., 2023), our proposed method can thus inspire these areas of research.

6. Limitations and future research

This study has a number of limitations. First, we only examined visual posts from five accounts which were present on two platforms and above an activity threshold. This limited scope may not provide a comprehensive understanding of the overall patterns and trends in climate change communication across all social media platforms, especially those from less active accounts or smaller advocacy organizations, and other social media platforms used heavily for climate advocacy (e.g., YouTube). Additionally, this study focused solely on climate change, therefore the visual categories derived from our clustering analysis can be different from those in other topics relevant to strategic communication and advocacy. Further, this study focused solely on visual content without taking into account embedded text in those images or accompanying captions on social media engagement. Textual elements contribute to the understanding of visual content, and not considering their role could result in a less comprehensive analysis.

To address these limitations, we propose a few promising future research directions. First, future research can incorporate embedded text as well as captions in analyzing visual and multimodal content to gain a more comprehensive understanding of how climate change visuals are associated with engagement. Second, to increase generalizability, it is crucial to sample visual content from a large number of advocacy accounts and beyond a single issue focus. We advocate for such an approach in order to reveal both topic-specific and topic-agnostic results. For example, our clustering analysis based on climate change visuals yielded five visual categories. Which of these categories are unique to climate change, and which are universal across many topics remains a valuable topic for future research. Lastly, future research can expand our analysis to investigate the convergence and divergence of visual content and features across more platforms.

7. Conclusion

The current study examines the visual characteristics and public engagement of climate change visual posts on Twitter and Instagram. Even though the five content categories are all present on both platforms, Instagram has significantly more content depicting nature landscape/wildlife, while Twitter has significantly more content on infographics/captioned image and visualizations. Such content divergence might be the main driver for observed platform-level visual feature differences such as specific colors, colorfulness, and feature complexity. By identifying how visual posts diverge or converge on Twitter and Instagram, our study offers practical insights for advocacy organizations to better understand the norms and expectations of each platform and to design effective strategic content for deeper user engagement. Methodologically, this study demonstrates the utility of computational visual analysis in strategic communication, where visuals play a prominent role.

Open science statement

Data and reproducible analysis transcript used in this study can be found in this OSF repository: https://osf.io/cvduk/..

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.pubrev.2024.102454.

References

Altheide, D. L. (2004). Media logic and political communication. *Political Communication, 21*(3), 293–296. https://doi.org/10.1080/10584600490481307
Argyris, Y. A., Wang, Z., Kim, Y., & Yin, Z. (2020). The effects of visual congruence on increasing consumers' brand engagement: An empirical investigation of influencer marketing on Instagram using deep-learning algorithms for automatic image classification. *Computers in Human Behavior, 112*, Article 106443.
Auxier, B., & Anderson, M. (2021). Social media use in 2021. Pew Research Center.
Bakhshi, S., & Gilbert, E. (2015). Red, purple and pink: The colors of diffusion on Pinterest. *PloS One, 10*(2), Article e0117148.
Bakhshi, S., Shamma, D. A., & Gilbert, E. (2014). Faces engage us: Photos with faces attract more likes and comments on Instagram. *In Proceedings of the SIGCHI Conference on Human factors in Computing Systems*, 965–974.
Berman, M. G., Hout, M. C., Kardan, O., Hunter, M. R., Yourganov, G., Henderson, J. M., & Jonides, J. (2014). The perception of naturalness correlates with low-level visual features of environmental scenes. *PloS One, 9*(12), Article e114572.
Blight, M. G., Ruppel, E. K., & Schoenbauer, K. V. (2017). Sense of community on Twitter and Instagram: Exploring the roles of motives and parasocial relationships. *Cyberpsychology, Behavior, and Social Networking, 20*(5), 314–319.
Böhler, H., Hanegraaff, M., & Schulze, K. (2022). Does climate advocacy matter? The importance of competing interest groups for national climate policies. *Climate Policy, 22*(8), 961–975.
Bonsón, E., & Ratkai, M. (2013). A set of metrics to assess stakeholder engagement and social legitimacy on a corporate Facebook page. *Online Information Review, 37*(5), 787–803.
Bossetta, M. (2018). The digital architectures of social media: Comparing political campaigning on Facebook, Twitter, Instagram, and Snapchat in the 2016 US election. *Journalism & Mass Communication Quarterly, 95*(2), 471–496.
Bossetta, M., & Schmøkel, R. (2022). Cross-platform emotions and audience engagement in social media political campaigning: Comparing candidates' Facebook and Instagram images in the 2020 US election. *Political Communication*, 1–21.
Burgess, J., & Matamoros-Fernández, A. (2016). Mapping sociocultural controversies across digital media platforms: One week of #gamergate on Twitter, YouTube, and Tumblr. *Communication Research and Practice, 2*(1), 79–96. https://doi.org/10.1080/22041451.2016.1155338
Canon, C. R., Boyle, D. P., & Hepworth, K. J. (2022). Mapping pathways to public understanding of climate science. *Public Understanding of Science, 31*(6), 766–783.
Center for Research on Environmental Decisions, & ecoAmerica. (2014). Connecting on climate: A guide to effective climate change communication.
Chapman, D. A., Corner, A., Webster, R., & Markowitz, E. M. (2016). Climate visuals: A mixed methods investigation of public perceptions of climate images in three countries. *Global Environmental Change, 41*, 172–182. https://doi.org/10.1016/j.gloenvcha.2016.10.003
Chen, Q., Min, C., Zhang, W., Wang, G., Ma, X., & Evans, R. (2020). Unpacking the black box: How to promote citizen engagement through government social media during the COVID-19 crisis. *Computers in Human Behavior, 110*, Article 106380.
Chon, M. G., & Kim, S. (2022). Dealing with the COVID-19 crisis: Theoretical application of social media analytics in government crisis management. *Public Relations Review, 48*(3), Article 102201.
Cleave, E., Arku, G., & Chatwin, M. (2017). Cities' economic development efforts in a changing global economy: Content analysis of economic development plans in Ontario. *Canada Area, 49*(3), 359–368.
Clark, J. M., & Paivio, A. (1991). Dual coding theory and education. *Educational Psychology Review, 3*(3), 149–210.
Dhanesh, G. S. (2017). Putting engagement in its PRoper place: State of the field, definition and model of engagement in public relations. *Public Relations Review, 43*(5), 925–933.
Duan, R., Zwickle, A., & Takahashi, B. (2022). Refining the application of construal level theory: Egocentric and nonegocentric psychological distances in climate change visual communication. *Environmental Communication, 16*(1), 92–107.

Farkas, X., & Bene, M. (2021). Images, politicians, and social media: Patterns and effects of politicians' image-based political communication strategies on social media. *The International Journal of Press/politics, 26*(1), 119–142.

Galloway, C. (2017). Blink and they're gone: PR and the battle for attention. *Public Relations Review, 43*(5), 969–977.

Gibbs, M., Meese, J., Arnold, M., Nansen, B., & Carter, M. (2015). # Funeral and Instagram: Death, social media, and platform vernacular. *Information, Communication & Society, 18*(3), 255–268.

Harold, J., Lorenzoni, I., Shipley, T. F., & Coventry, K. R. (2016). Cognitive and psychological science insights to improve climate change data visualization. *Nature Climate Change, 6*(12), 1080–1089.

Hart, P. S., & Feldman, L. (2016). The impact of climate change-related imagery and text on public opinion and behavior change. *Science Communication, 38*(4), 415–441.

Hasler, D., & Suesstrunk, S. E. (2003). Measuring colorfulness in natural images. *Human Vision and Electronic Imaging, VIII*(5007)), 87–95. https://doi.org/10.1117/12.477378

Hopke, J. E., & Hestres, L. E. (2018). Visualizing the Paris climate talks on Twitter: Media and climate stakeholder visual social media during COP21. *Social Media+ Society, 4*(3), 2056305118782687.

Huang, J., Kumar, S. R., Mitra, M., Zhu, W. J., & Zabih, R. (1999). Spatial color indexing and applications. *International Journal of Computer Vision, 35*(3), 245–268.

IPCC. (2022). Climate change 2022: Impacts, adaptation and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change. Cambridge University Press.

Ji, Y. G., Chen, Z. F., Tao, W., & Li, Z. C. (2019). Functional and emotional traits of corporate social media message strategies: Behavioral insights from S&P 500 Facebook data. *Public Relations Review, 45*(1), 88–103.

Joo, J., Li, W., Steen, F. F., & Zhu, S. C. (2014). Visual persuasion: Inferring communicative intents of images. *In Proceedings of the IEEE Conference on computer Vision and Pattern Recognition*, 216–223.

Joo, J., Steen, F. F., & Zhu, S. C. (2015). Automated facial trait judgment and election outcome prediction: Social dimensions of face. *In Proceedings of the IEEE International Conference on computer Vision*, 3712–3720.

Joo, J., & Steinert-Threlkeld, Z. C. (2022). Image as data: Automated content analysis for visual presentations of political actors and events. *Computational Communication Research, 4*(1).

Kanuri, V. K., Hughes, C., & Hodges, B. T. (2023). Standing out from the crowd: When and why color complexity in social media images increases user engagement. *International Journal of Research in Marketing*.

Kreiss, D., Lawrence, R. G., & McGregor, S. C. (2018). In their own words: Political practitioner accounts of candidates, audiences, affordances, genres, and timing in strategic social media use. *Political Communication, 35*(1), 8–31. https://doi.org/10.1080/10584609.2017.1334727

Krishna, A. (2021). Understanding the differences between climate change deniers and believers' knowledge, media use, and trust in related information sources. *Public Relations Review, 47*(1), Article 101986.

Iyer, A., Webster, J., Hornsey, M. J., & Vanman, E. J. (2014). Understanding the power of the picture: The effect of image content on emotional and political responses to terrorism. *Journal of Applied Social Psychology, 44*(7), 511–521.

Labrecque, L. I., & Milne, G. R. (2012). Exciting red and competent blue: The importance of color in marketing. *Journal of the Academy of Marketing Science, 40*(5), 711–727. https://doi.org/10.1007/s11747010-0245-y

Lee, Y.-J. (2021). Liked on Facebook, liked for real?: Nonprofits' online popularity and financial performance. *Nonprofit Management and Leadership, 31*(3), 609–621. https://doi.org/10.1002/nml.21447

Lee, N. M., VanDyke, M. S., & Cummins, R. G. (2018). A missed opportunity?: NOAA's use of social media to communicate climate science. *Environmental Communication, 12*(2), 274–283.

León, B., Negredo, S., & Erviti, M. C. (2022). Social engagement with climate change: principles for effective visual representation on social media. *Climate Policy, 22*(8), 976–992.

Li, Y., & Xie, Y. (2020). Is a picture worth a thousand words? An empirical study of image content and social media engagement. *Journal of marketing research, 57*(1), 1–19.

Lu, Y., & Pan, J. (2022). The pervasive presence of Chinese government content on Douyin trending videos. *Computational Communication Research, 4*(1).

Lu, Y., & Peng, Y. (2024). *The mobilizing power of visual media across stages of social-mediated protests* (pp. 1–28). Political Communication.

Lu, Y., & Shen, C. (2023). Unpacking multimodal fact-checking: Features and engagement of fact-checking videos on Chinese TikTok (Douyin). *Social Media+ Society, 9*(1), 20563051221150406.

Manikonda, L., Meduri, V.V., & Kambhampati, S. (2016). Tweeting the mind and instagramming the heart: Exploring differentiated content sharing on social media. In Tenth international AAAI conference on web and social media.

Manovich, L. (2016). The science of culture? Social computing, digital humanities and cultural analytics. Journal of Cultural Analytics, 1(1).

McClain, C., Widjaya, R., Rivero, G., & Smith, A. (2021). The behaviors and attitudes of US adults on Twitter. Pew Research Center.

McKie, D., & Galloway, C. (2007). Climate change after denial: Global reach, global responsibilities, and public relations. *Public Relations Review, 33*(4), 368–376.

McShane, L., Pancer, E., Poole, M., & Deng, Q. (2021). Emoji, playfulness, and brand engagement on twitter. *Journal of Interactive Marketing, 53*(1), 96–110.

Men, L. R., & Tsai, W. H. S. (2014). Perceptual, attitudinal, and behavioral outcomes of organization–public engagement on corporate social networking sites. *Journal of Public Relations Research, 26*(5), 417–435.

Men, L. R., & Tsai, W. H. S. (2015). Infusing social media with humanity: Corporate character, public engagement, and relational outcomes. *Public Relations Review, 41*(3), 395–403.

Messaris, P. (1997). *Visual Persuasion: The Role of Images in Advertising*. https://doi.org/10.4135/9781452233444

Messaris, P., & Abraham, L. (2001). The role of images in framing news stories. In S. D. Reese, O. H. Jr Gandy, & A. E. Grant (Eds.), *Framing public life: Perspectives on media and our understanding of the social world* (pp. 215–226). Lawrence Erlbaum Associates Publishers.

Molder, A. L., Lakind, A., Clemmons, Z. E., & Chen, K. (2022). Framing the global youth climate movement: a qualitative content analysis of Greta Thunberg's moral, hopeful, and motivational framing on Instagram. *The International Journal of Press/politics, 27*(3), 668–695.

Mooseder, A., Brantner, C., Zamith, R., & Pfeffer, J. (2023). Social) Media logics and visualizing climate change: 10 Years of# climatechange images on Twitter. *Social Media+ Society, 9*(1), 20563051231164310.

Moser, S. C. (2010). Communicating climate change: history, challenges, process and future directions. *Wiley Interdisciplinary Reviews: Climate Change, 1*(1), 31–53.

Nabi, R. L. (2003). Exploring the framing effects of emotion: Do discrete emotions differentially influence information accessibility, information seeking, and policy preference? *Communication Research, 30*(2), 224–247.

Niederer, S. (2018). Networked images:Visual methodologies for the digital age. Amsterdam: Hoge school van Amsterdam.

O'Neill, S. J., & Nicholson-Cole, S. (2009). Fear won't do it" promoting positive engagement with climate change through visual and iconic representations. *Science communication, 30*(3), 355–379.

O'Neill, S.J. (2017). Engaging the public with climate change: communication and behaviour change. Routledge.

O'Neill, S. J. (2013). Image matters: Climate change imagery in US, UK and Australian newspapers. *Geoforum, 49*, 10–19.

O'Neill, S. J., Boykoff, M., Niemeyer, S., & Day, S. A. (2013). On the use of imagery for climate change engagement. *Global Environmental Change, 23*(2), 413–421.

Patiño-Escarcina, R. E., & Costa, J. A. F. (2008). The semantic clustering of images and its relation with low level color features. In 2008 (August) *IEEE International Conference on Semantic Computing*, 74–79.

Pearce, W., Özkula, S. M., Greene, A. K., Teeling, L., Bansard, J. S., Omena, J. J., & Rabello, E. T. (2020). Visual cross-platform analysis: Digital methods to research social media images. *Information, Communication & Society, 23*(2), 161–180.

Peng, Y. (2017). Time travel with one click: Effects of digital filters on perceptions of photographs. *In CHI (pp.*, 6000–6011.

Peng, Y. (2018). Same candidates, different faces: Uncovering media bias in visual portrayals of presidential candidates with computer vision. *Journal of Communication, 68*(5), 920–941.

Peng, Y. (2021). What makes politicians' Instagram posts popular? Analyzing social media strategies of candidates and office holders with computer vision. *The International Journal of Press/Politics, 26*(1), 143–166.

Peng, Y. (2022). Athec: A Python library for computational aesthetic analysis of visual media in social science research. *Computational Communication Research, 4*(1).

Peng, Y., & Jemmott, J. B. (2018). Feast for the eyes: Effects of food perceptions and computer vision features on food photo popularity. *International Journal of Communication, 19328036*, 12.

Petty, R. E., & Cacioppo, J. T. (1986). *The elaboration likelihood model of persuasion* (pp. 1–24). New York: Springer,.

Pew Research Center. (2023). *Social Media and news Factory Sheet*. ⟨https://www.pewresearch.org/journalism/fact-sheet/social-media-and-news-fact-sheet/⟩.

Pieters, R., Wedel, M., & Batra, R. (2010). The stopping power of advertising: Measures and effects of visual complexity. *Journal of Marketing, 74*(5), 48–60. https://doi.org/10.1509/jmkg.74.5.048

Pressgrove, G., Janoske, M., & Haught, M. J. (2018). Editors' letter: New research and opportunities in public relations and visual communication. *Public Relations Review, 44*(3), 317–320.

Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: Is beauty in the perceiver's processing experience? *Personality and Social Psychology Review, 8*(4), 364–382.

Rogers, R. (2021). Visual media analysis for Instagram and other online platforms. *Big Data & Society, 8*(1), 20539517211022370.

Rouw, R., Kosslyn, S. M., & Hamel, R. (1997). Detecting high-level and low-level properties in visual images and visual percepts. *Cognition, 63*(2), 209–226.

Sevin, E. (2016). Branding cities in the age of social media: A comparative assessment of local government performance. *Social Media and Local governments: Theory and Practice*, 301–320.

Schäfer, M. S. (2020). News media images of climate change: Reviewing the research. In D. C. Holmes, & L. M. Richardson (Eds.), *Research handbook on communicating climate change* (pp. 143–152). Edward Elgar.

Schaeffer, K. (2021). 7 facts about Americans and Instagram. Pew Research Center.

Schneider, B. (2014). *Red futures: the colour red in scientific imagery of climate change. Disaster as image. Iconographies and Media Strategies across Europe and Asia.* (pp. 183–194) Regensburg: Schnell & Steiner,.

Schneider, B., & Nocke, T. (2018). The feeling of red and blue—A constructive critique of color mapping in visual climate change communication. *Handbook of Climate Change Communication: Vol 2: Practice of Climate Change Communication*, 289–303.

Sharma, M., & Peng, Y. (2023). How visual aesthetics and calorie density predict food image popularity on Instagram: A computer vision analysis. *Health Communication*, 1–15.

Sinatra, G. M., & Seyranian, V. (2015). Warm change about hot topics: The role of motivation and emotion in attitude and conceptual change about controversial science topics. *In Handbook of educational psychology* (pp. 259–270). Routledge,.
Smith, B. G., & Gallicano, T. D. (2015). Terms of engagement: Analyzing public engagement with organizations through social media. *Computers in Human Behavior, 53*, 82–90.
Steffan, D. (2020). Visual self-presentation strategies of political candidates on social media platforms: A comparative study. *International Journal of Communication, 14*, 23.
Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*(1), 97–136.
Tuch, A., Kreibig, S., Roth, S., Bargas-Avila, J., Opwis, K., & Wilhelm, F. (2011). The role of visual complexity in affective reactions to webpages: Subjective, eye movement, and cardiovascular responses. *IEEE Transactions on Affective Computing, 2*(4), 230–236.
Valenzuela, S., Piña, M., & Ramírez, J. (2017). Behavioral effects of framing on social media users: How conflict, economic, human interest, and morality frames drive news sharing. *Journal of Communication, 67*(5), 803–826.
Wang, Y., & Yang, Y. (2020). Dialogic communication on social media: How organizations use Twitter to build dialogic relationships with their publics. *Computers in Human Behavior, 104*, Article 106183.
Wen, T.J., Peng, Y., & Yang, J. (2023). A computer vision methodology to predict brand personality from image features. Journal of Advertising. Advance online publication.
Zhang, H., & Peng, Y. (2021). Image clustering: An unsupervised approach to categorize visual data in social science research. Sociological Methods & Research, 00491241221082603.
Zhou, B., Lapedriza, A., Khosla, A., Oliva, A., & Torralba, A. (2017). Places: A 10 million image database for scene recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 40*(6), 1452–1464.
Ke, Y., Tang, X., & Jing, F. (2006). The design of high-level features for photo quality assessment. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 419–426).