Political Communication

ISSN: 1058-4609 (Print) 1091-7675 (Online) Journal homepage: www.tandfonline.com/journals/upcp20

# The Mobilizing Power of Visual Media Across Stages of Social-Mediated Protests

Yingdan Lu & Yilang Peng

**To cite this article:** Yingdan Lu & Yilang Peng (2024) The Mobilizing Power of Visual Media Across Stages of Social-Mediated Protests, Political Communication, 41:4, 531-558, DOI: 10.1080/10584609.2024.2317951

**To link to this article:** https://doi.org/10.1080/10584609.2024.2317951

POLITICAL COMMUNICATION
2024, VOL. 41, NO. 4, 531–558
https://doi.org/10.1080/10584609.2024.2317951

Routledge
Taylor & Francis Group



# The Mobilizing Power of Visual Media Across Stages of Social-Mediated Protests

Yingdan Lu [a] and Yilang Peng [b]

[a]Department of Communication Studies, Northwestern University, Evanston, USA; [b]Department of Financial Planning, Housing and Consumer Economics, University of Georgia, Athens, USA

**ABSTRACT**

The popularity of camera phones, the availability of photo-editing apps, and the rise of visually oriented social media platforms have made it convenient for citizens to produce and circulate visual content in contentious politics. While scholars have increasingly recognized the role of visuals in mobilizing social-mediated protests, how different types of visuals affect message engagement across different stages of protests remains underexplored. For this study, we analyzed approximately ten million tweets from Twitter for three social-mediated protests (Black Lives Matter, Stop Asian Hate, and Women's March). We found that posts with images and videos generally attracted more audience engagement than their textual counterparts. Unpacking the role of visual media across different modalities and stages of social-mediated protests, we found that the superior effects of visuals were generally more pronounced during the ignition phase of the protest than the periods before and after. By applying unsupervised image clustering on millions of protest visuals, we systematically established four common visual content categories: crowd-based protest photos, non-crowd-protest human photos, non-human photos, and non-photograph visuals. We revealed heterogeneous effects on audience engagement across content categories and protests, and explored these categories through qualitative analysis of most-engaged visuals. These findings enrich our understanding of the mobilizing power of visual media in social movements and shed light on effective communication strategies regarding social inequalities.

**KEYWORDS**

Visual media; social-mediated protest; social movement; social media; computer vision; audience engagement; Twitter; temporality; mobilization

## Introduction

The COVID-19 pandemic not only resulted in the loss of human lives around the globe but also exacerbated existing social inequality, increased discrimination and prejudice, and sparked a series of social protests. Amid these crises, scholars are increasingly recognizing the importance of visuals because of the key role of social media in mobilizing protests. The popularity of camera phones, the availability of photo-editing apps, and the rise of visually oriented social media platforms allow citizens to conveniently produce and circulate visual content in contentious politics (Andén-Papadopoulos, 2014; Bock, 2016; Jenzen et al., 2021; Mattoni & Teune, 2014; Peng, Lock, et al., 2023a). Citizen photographers and videographers frequently participate in documenting violence and crises (Andén-Papadopoulos, 2014; Bock,

**CONTACT** Yilang Peng yilang.peng@uga.edu Department of Financial Planning, Housing and Consumer Economics, University of Georgia, 120 Barrow Hall, 115 DW Brooks Dr, Athens, GA 30602, USA

2016). Activists circulate online memes and viral videos to challenge predominant discourses (Bayerl & Stoynov, 2016). Ranging from videos that document police brutality to photographs that show the solidarity of protesters to captioned images that share anger and hope, visual content plays an essential role in mobilizations on social media in times of crisis.

An increasing body of scholarship has investigated how visuals mobilize protests and social movements (Casas & Williams, 2019; Cornet et al., 2017; Jenzen et al., 2021; Joo & Steinert-Threlkeld, 2022; Lewin & Jenzen, 2023; Tait, 2023). Visuals help movement messages propagate and recruit new participants to online activism (Casas & Williams, 2019). Experimental research has demonstrated that images of protests can attract viewers' attention and shape their attitudes and participatory intentions (Arpan et al., 2006; Geise, Heck, et al., 2021; Geise, Panke, et al., 2021). Meanwhile, research in media effects has shown that visual media has greater power in provoking emotions, enhancing credibility, and attracting attention than other textual formats (Casas & Williams, 2019; Slovic et al., 2017; Sundar et al., 2021). These findings suggest that visuals generally play an essential and advantageous role in catalyzing online protests.

While prior research highlights how visuals attract movement engagement, we focus on three important gaps in understanding the mobilizing power of visuals in social-mediated protests. First, compared to research that focuses on the visual modality of visual content, we separated videos from static images as they possess different modality features, and we investigated how visuals in different modalities attract online engagement with protest messages. Second, our investigation highlighted *temporality* and examined the effects of visual media across various stages of social-mediated protests. Multiple scholars have studied the temporal dynamics of social movements and traced how protests unfold over time (F. L. Lee & Chan, 2018; Tarrow, 1993). We argue that visual messages provide different functions across the stages of a social-mediated protest. Additionally, protests make use of diverse frames and types of visuals, such as the portrayal of crowds (Joo & Steinert-Threlkeld, 2022), which can function differently in affecting users' engagement with content. We propose that it is important to look beyond modality to examine how different visual categories affect the online engagement of social protest.

For this study, we collected approximately ten million social media posts related to three massive social-mediated protests: the Black Lives Matter (BLM) protest in 2020, the Stop Asian Hate (SAH) protest in 2021, and the Women's March (WM) in 2017. We refer to "social-mediated protests" as protests that gain traction in responses to grievances or crises, with their organization and dissemination being facilitated by social media. Using regression analysis, we investigated the effectiveness of images and videos in attracting audience engagement as well as across different stages of social-mediated protests. Through combining theory and large-scale unsupervised image clustering of protest visuals, we systematically established common visual content categories, their presence across protests, and their effects on audience engagement with protest messages. Through qualitative analysis of most-engaged visuals, we further explore the content and strategies of these different content categories and their association with post engagement. Our study advances existing research by providing a more comprehensive examination of the role of visuals in online movements and by providing a comparative understanding of visual effects across three movements.

## The Role of Visual Media in Mobilizing Social-Mediated Protests

Many scholars have observed a transformation in the organization of contemporary protests and collective actions due to the emergence of social media platforms (Benski et al., 2013; Bennett & Segerberg, 2012). The development of information and communication technologies has enabled individuals to participate in social protests with low-cost online actions (Earl et al., 2015) and scaled up mobilization by rapidly connecting disconnected individuals and their actions (Bennett & Segerberg, 2012; Earl & Kimport, 2011). Social media platforms, in particular, have been leveraged in contemporary social protests, such as the Arab Spring in the Middle East (Howard et al., 2011) and Occupy Wall Street in the United States (Theocharis et al., 2015), because of their multifaceted affordances in mediating and mobilizing movements. Prior research has found that social media platforms enable rapid exchange of protest information (Jost et al., 2018; Zhuravskaya et al., 2020), accelerate the formation of protest communities (Clothey et al., 2016; Earl & Kimport, 2011), and attract international alliances for protests (Garrett, 2006; Howard et al., 2011; P. S. Lee et al., 2015; Lynch, 2011). Scholars have also introduced new concepts to conceptualize activism facilitated by digital media. For example, "connective action" (Bennett & Segerberg, 2012) and "social-mediated movements" (A. Zhou & Yang, 2021) occur when digital technologies enable loosely connected individuals to engage in collective actions without necessarily forming traditional organizations with long-term goals.

Despite the acknowledgment of the role of social media, one affordance of social media is rarely explored for its role in mobilizing social-mediated protests – the creation and dissemination of visual content to support social-mediated protests. When documenting their lives, social media users can create visual content, with photographic images, illustrations, videos, and other visual content accompanied by textual information (Lewin & Jenzen, 2023). Additionally, activists may craft tangible visual elements in the offline realm, including mural art and street signage, as a means to visually communicate their identities and goals (Tait, 2023) which they then share on social media. Social media is widely available on mobile devices, which enables individuals to easily capture, document, and post what they experience or observe in protests and social movements. The use of hashtags allows protest participants to contribute their own stories in visual forms like photographs and cartoons to shape hashtag activism for wider engagement (Yang, 2016, p. 16). Protest visuals are prevalent on social media; for example, Zhang and Pan (2019) find that 56.9% of 10,000 annotated protest posts from the Chinese social media platform Weibo contain visuals. The significant impact that visuals have on the development of social movements has prompted scholars to conceptualize social movements as "visual phenomena" (Mattoni & Teune, 2014).

Meanwhile, existing theories and studies suggest that visual media can be more powerful than text in attracting online engagement. Visual media such as photos and videos resemble indexical representations of events or objects in reality, making viewers more likely to believe the portrayals compared to text messages (Messaris, 1997). Empirical studies have documented the superior effects of visual media in enhancing credibility, provoking emotions, and attracting attention compared with their textual counterparts (Barry, 1997; Casas & Williams, 2019; Grabe & Bucy, 2009; Slovic et al., 2017; Sundar et al., 2021). Consequently, visual posts containing images or videos are more likely to be shared and become viral on social media compared with posts without such content (Brown & Mourão, 2021; Bruni et al., 2012).

We expect that visuals will have a similar positive effect on social media engagement for social-mediated protests. Analyzing tweets about a BLM protest, Casas and Williams (2019) identified a "general image effect," whereby messages with images attract more attention and a larger number of new participants to the protest on social media compared to plain-text messages. Studies like Neumayer and Rossi (2018) also find that sharing videos positively predicts the visibility of protest-related posts. Yet, whether the general image effect applies only to particular protests or can be extrapolated to a wide range of social protests is unknown. Other studies examining the effects of visual media on social mobilization have also been limited to the use of visuals to estimate protest sizes (e.g., Sobolev et al., 2020), without investigating how they further mobilize engagement with online protest messages.

Prior research has often focused on a single type of visual media (**image** or **video**) or considered the general effects of visual media. However, the Modality – Agency – Interactivity – Navigability (MAIN) model (Sundar, 2008) suggests that as the mode of message presentation becomes richer from text to image to video, there are more realism heuristics provided for recipients to perceive the message as credible (Sundar et al., 2021). In social protests, the effects of videos may differ from those of images, as videos provide more complete representations of the scene (e.g., including sound and motion) and a more immersive viewing experience. Despite a growing body of research demonstrating the superiority of videos over text messages in shaping beliefs (Wittenberg et al., 2021; Young et al., 2018), very little research compares videos and static images to understand their effects in inducing engagement, particularly in the protest context. Therefore, both static images and videos are likely to attract more engagement with protest messages than text on social media, but further investigation of their differences is necessary.

We focus on two specific types of audience engagement on social media: **likes** and **retweets**. On news websites and social media, users can engage with messages through reading, liking, commenting, and resharing. These different engagement actions represent varying levels of effort and publicness (Aldous et al., 2019; Molina et al., 2022), from low to high, and can be prompted by the same content in different ways (Molina et al., 2022; Tenenboim & Cohen, 2015). These engagement behaviors can differentially affect the reinforcement of preexisting opinions, the perceived importance of the content, and the dissemination of the post (Wang et al., 2022; Zell & Moeller, 2018). Likes and retweets are widely used to quantify the visibility or virality of social media posts (Kim, 2018; Lu & Pan, 2021), and both are significant measures of online protest engagement. "Liking" a protest post is a low-cost action that expresses a range of affective responses, but the algorithms push the most engaged protest content throughout the liker's network (Gerlitz & Helmond, 2013). Retweeting, as a higher-cost and more public action than liking, not only facilitates the spread of the protest message but also identifies the retweeter to leaders and members of the movement as a new supporter (Casas & Williams, 2019). In summary, we propose:

**H1:** Compared with posts without visuals, protest messages with static images will attract more likes (H1a) and retweets (H1b).

**H2:** Compared with posts without visuals, protest messages content with videos will attract more likes (H2a) and retweets (H2b).

**RQ1:** Do protest messages with static images have different engagement effects compared with protest messages with videos?

## The Role of Visual Media Across Stages of Social-Mediated Protests

While scholars acknowledge the potential of digital media in facilitating the initiation of protests and, potentially, social movements, a critical concern arises in distinguishing between protest campaigns and fully-fledged social movements. Not every protest necessarily signifies the birth of a social movement, and social media platforms often struggle to maintain sustained long-term public attention and discourse (Benski et al., 2013). Some movements, like BLM, have a more extensive historical trajectory, whereas others, such as SAH and WM, appear to emerge in response to specific events and subsequently wane with less potential to shape social movements, even though they may attract significant attention. Consequently, we focus on social-mediated protests that may or may not form social movements, and it becomes necessary to consider the temporal dynamics of social media attention and online mobilization of these protests.

In learning the temporal dynamics of protests and how protests evolve over time (F. L. Lee & Chan, 2018; Tarrow, 1993; A. Zhou & Yang, 2021), some argue that it is important to consider long-, medium-, and short-term cycles and to observe how one protest is connected to others in the same sociopolitical era (Della Porta & Mattoni, 2014; F. L. Lee & Chan, 2018). Others point out that social movements often unfold over time and are shaped by different social, political, and technological forces at different stages (Della Porta & Mattoni, 2014; Koopmans, 2004; Tarrow, 1993). For example, Tarrow (1993) summarized five stages of a protest cycle: "heightened conflict," "geographic and sectoral diffusion," "social movement organizations," "new frames of meaning," and "expanding repertoires of contention." González-Bailón et al. (2011) demonstrated that protests often need to diffuse from core to periphery, and participants often observe an accumulation of signals that are activated and become involved in protests.

It is important to consider the temporality of social-mediated protests because the role of technology can change across different stages of protests. Prior research on protests in Egypt and Israel reveals that social media platforms like Facebook played a critical role in the early stages of the protests, when a core group of activists coalesced and propagated messages to the initial supporters. As the protest progressed, online activities gave way to offline actions, and the protest's success increasingly hinged on mainstream media coverage to recruit new participants and secure broader public support (Della Porta & Mattoni, 2014; Lev-On, 2020).

Some works have also explicitly addressed the stages of social protests. Howard and Hussain (2011) identified multiple phases in their analysis of the Arab Spring, beginning with the "preparation" phase where digital media allowed activists to connect and establish political goals around shared grievances. The "ignition" phase followed, which was typically triggered by a tragic incident inciting public outrage and leading to a climax with both online and offline participation. Echoing this work, LeFebvre and Armstrong (2018) further termed the temporality into three phases: pre-storm, storm, and post-storm. During the preparation/pre-storm phase, activists form online social networks and establish their political objectives. During the ignition/storm phase, a symbolic event occurs and mobilizes

the public around grievances and feelings of injustice. Finally, the post-storm phase sees a dramatic decrease in online volume and attention, and protesters shift their focus to offline settings while strategically using online networks to organize protests. In sum, this line of literature highlights the challenge of sustaining public interest and engagement in the long term – a powerful event typically triggers attention, and then dies down quickly.

Considering the short-lived, cyclical nature of online attention, we focus on the type of social-mediated protests that involve a **pre-ignition phase**, during which a long-term issue or grievance may not receive constant attention from the public, followed by an **ignition phase**, in which an external, usually outrage-provoking, event triggers a surge of attention online over a relatively short period of time, and a **post-ignition phase** when public attention dies down.

We argue that visuals may play different roles in different phases of social protests. Their role may be particularly crucial during the ignition phase of a protest. Visual messages, which provide viewers with graphic experiences of the event and vividly broadcast violence, can effectively provoke emotions and create a spectacle, thereby contributing to the rapid increase in online attention, and emotional mobilization, with intensive expressions of outrage, grievances, and solidarity that are more commonly seen in the ignition phase (Howard & Hussain, 2011; LeFebvre & Armstrong, 2018). For example, pictures of Aylan Kurdi – a child refugee who died en route to Europe – sparked global attention to the Syrian refugee crisis on social media (Slovic et al., 2017; Smith et al., 2018). In a similar vein, the footage of George Floyd, an unarmed Black man being murdered by a white police officer Derek Chauvin, sparked immediate public outrage and was widely shared on social media. A survey revealed that during the week following the murder, there was a significant increase in feelings of anger and sadness among the U.S. public (Eichstaedt et al., 2021).

The emotional mobilization effects of visual messages can be short-lived. For example, while the pictures of Aylan Kurdi provoked large-scale empathy and behavioral changes such as donations and search queries, public attention waned within only a few weeks (Slovic et al., 2017). In summary, the ignition phase is often linked with heightened emotional experiences, and visual media can generate immediate emotional responses and have relatively short-lived effects. Therefore, we anticipate that

**H3.** The superior effects of images and videos in attracting more likes and retweets than text will be more pronounced during the ignition phase of a social-mediated protest compared to the pre- and post-ignition periods.

## Visual Content Categories and Their Effects on Audience Engagement

In addition to the potential variations across different temporal periods, visuals are also diverse in content, calling for more research to uncover the granular components of visuals that affect mobilizing protests. Visuals created by different actors with different purposes may yield different visual framings, emotions, elements, and features. Research in political communication has thus examined how content-level features of visuals could affect political participation, such as propensity to seek

political information (Ryan, 2012), perceptions of politicians (Peng, 2018; Shah et al., 2016), and voting preferences (Brader, 2005; Horiuchi et al., 2012).

In the context of social protests, scholars have noted the heterogeneity of visual media and their differential effects on engagement with protest messages. For example, one strand of research focuses on how protest visuals that vary in emotion lead to different levels of participation. Casas and Williams (2019) find that images arousing enthusiasm and fear gather online attention to and participation in online protests. Geise, Heck, et al. (2021) exposed participants to different types of protest-related news photos, and found that individuals are more likely to participate online if they perceive the images as surprising or highly emotional. Another experimental study (Geise, Panke, et al., 2021) examined protest-related news images and found that individuals who viewed negatively valenced images for a longer period of time were more willing to participate in social protests, but this association did not occur for positively valenced images.

Another line of research on visual content examines specific signals, portrayals, or broader content categories occurring in protest visuals and how those lead to protest participation. Research in this area started by analyzing visuals in protest-related news coverage, for example, the occurrence of conflict and violence when reporting on social protests (Baylor, 1996), and comparing the positions of officials and protesters (Corrigall-Brown & Wilkes, 2012). For social-mediated protests, it is more important to unpack visual content because different actors can post about the protest on social media simultaneously (Rossi et al., 2016), resulting in different visual content being created for different purposes (promoting or suppressing the protest). Qualitative studies and quantitative content analyses have identified some key visual content in social protests, such as the portrayal of spectacle crowds for WM on Instagram (Brown, 2022), the use of flags and drawings of martyrs by Gezi protesters in Turkey on Twitter (Ozduzen & McGarry, 2020), and depictions of peaceful protests for #LetThemStay in Australia (Hall et al., 2018). Nevertheless, constrained by their focus on single protest cases and the limitations of human-based content analysis, these studies were not able to provide a systematic typology of content categories of user-generated visual content across social-mediated protests.

Recent breakthroughs in deep learning and computer vision enable researchers to analyze the visual content of social protests with higher granularity and generalizability using scalable data. Most existing research of this line used supervised learning with human-annotated labels to understand the visual features of social protests. From a content perspective, consistent with prior literature, Joo and Steinert-Threlkeld (2022) found Twitter images about protests are more likely to use *crowds* for framing than individuals. Findings on crowds and violence among protest visuals also imply the prevalence of *human presence* in shaping protest visuals. As for visual formats, Allen et al. (2021) found that nearly 50% of SAH-related Twitter images are *photographs*, rather than other formats such as illustrations. However, as no comparative work has synthesized visual categories across protests, it remains unclear whether the found content features are consistent across social-mediated protests, or whether distinct categories are used. In addition, although both static images and videos can index the reality of social protests, videos possess a richer mode of message presentation (Sundar, 2008), and could be produced in different ways (e.g., by users' smartphones) from static images that could be professional photographs sourced from news outlets (Neumayer & Rossi, 2018). Meanwhile, as participants in the ignition phase of a protest may express outrage,

grievances, and solidarity intensively, the content of visuals may also have temporal characteristics. However, as prior research does not provide directional evidence, we pose the following research questions:

**RQ2.** What content categories of visual media are circulated in protest posts on social media (RQ2a)? How are these categories different between image posts and video posts (RQ2b), or across different phases of social-mediated protests (RQ2c)?

For visual posts with different categories identified in RQ2, we expect that they have differential effects on audience engagement. The portrayal of crowd protests such as the most popular social media image during the Gezi protests, for example, presents a more comprehensive illustration of the protest than other types of visuals (Ozduzen & McGarry, 2020). As crowd-related visuals can contain conflicts, violence, and confrontations, they may elicit more emotion and attract more engagement from the public than other content (Valenzuela et al., 2017), in an effect similar to the cheerleader effect found in group pictures (Walker & Vul, 2014). However, no comparative analyses have validated the effect of crowds in other protests. Photographic images, which have a high level of realism cues, are associated with a higher perceived engagement with the content (Hameleers et al., 2020; Li & Xie, 2020; Sundar, 2008). Prior research also suggests that the presence of humans is associated with more engagement on social media (Bakhshi et al., 2014; Li & Xie, 2020; Lu & Shen, 2023; Peng, 2021). Thus, it is reasonable to expect that the differential effects of visual categories on audience engagement may also extend to other contexts, including social protests. However, as no systematic analyses have validated these findings across social-mediated protests, we propose the following question:

**RQ3:** How do different visual categories predict likes and retweets of the protest posts?

## Case Selection of Social-Mediated Protests

To investigate the mobilizing power of visual media, we selected cases that meet multiple criteria. We focused on social protests that are pervasive and influential on social media, where visual media are powerful, protests can reach a wider audience, and online engagement can be traced and quantified. Based on our conceptualization regarding temporality, we identified social-mediated protests that underwent a pre-ignition phase, during which public attention to them was not particularly high. We selected cases that experienced a significant offline triggering event, which caught widespread public attention and generated a large online momentum for a relatively short period of time. This enables us to compare different stages of a protest over a short time span and trace what roles visual media play in this process.

We also aim to ensure that the selected cases are somewhat comparable in other aspects. These aspects include having a triggering event that occurred in the United States, focusing on injustices and disparities among social groups, and utilizing Twitter as one of the primary tools for mobilization and coordination. Consistent with our theoretical reasoning,

we identified three social-mediated protests that extensively used Twitter for protest coordination and sparked intense discussions on the platform following one major event – the WM in 2017, BLM in 2020, and SAH in 2021.

Over three million women across the United States took to the streets to advocate for social justice and gender equality in the WM. The triggering event was the inauguration of Donald Trump on January 20, 2017, who had expressed misogynistic views and advocated for policies that threatened women's rights. The hashtag #WomensMarch, calling women to march and unite for transformative social change, quickly went viral and became a trending topic on Twitter, attracting millions of users to join in the conversation and express their support for the protest (McDuffie & Ames, 2021).

The BLM movement originated in 2013 and has accumulated sustained public attention in response to numerous deaths of African Americans by police brutality. The movement spiked after the murder of George Floyd, a Black man killed by a White police officer, on May 25, 2020. A total of 8.8 million tweets with the hashtag #BlackLivesMatter were made on May 28, and an average of three million tweets with the same hashtag were posted during the first two weeks after Floyd's death (Anderson et al., 2020).

The SAH protest emerged as a response to rising anti-Asian discrimination, crime, and violence during the COVID-19 pandemic. The protest gained initial traction after the killing of Vicha Ratanapakdee on January 28, 2021, and exploded following the tragic Atlanta spa shootings on March 16, 2021. This event sparked significant online mobilization to combat anti-Asian hate on Twitter, with more than five million tweets posted within a month related to #StopAsianHate (Fan et al., 2021).

Although WM, BLM, and SAH share many similarities, they also exhibit significant differences in aspects such as primary goals, protest size, and duration. For example, the issues addressed by the BLM and WM protests, racialized police brutality and gender inequality respectively, have been already widely discussed before the protests gained momentum years before their triggering events. The similarities and differences across protests enable us to establish comparable results and understand the patterns of visual presentation within different protests in our dataset.

## Data: Twitter Protest Data

We examined the research questions by collecting social media posts from Twitter, a platform commonly used in contemporary moments. Twitter affords people a better understanding of public events (McClain et al., 2022) and has been widely used for information sharing and coordination in protests (Earl et al., 2013; Ozduzen & McGarry, 2020; Steinert-Threlkeld, 2017; Theocharis et al., 2015). Using the most widely circulated hashtag for each protest (#WomensMarch, #BlackLivesMatter, and #StopAsianHate), we retrieved historical tweets through the Twitter API for Academic Research. To address our research questions on temporality, we collected original posts with hashtags from the month before the date of the largest mobilization to the third month after the largest offline protest. This provided us with a four-month window to analyze the dynamics of visual usage. Table 1 provides an overview of the data collection. Nearly 8 million of the original posts were created under the #BlackLivesMatter hashtag, followed by almost 1.4 million original posts and 0.8 million original posts under the #WomensMarch

**Table 1.** Overview of data collection.

| | #BlackLivesMatter | #WomensMarch | #StopAsianHate |
|---|---|---|---|
| Time of the triggering event | May 25, 2020 | Jan. 20, 2017 | March 16, 2021 |
| Time for data collection | Apr. 25–Aug. 25, 2020 | Dec. 21, 2016–Apr. 21, 2017 | Feb. 16–June 16, 2021 |
| Number of posts | 7,791,488 | 1,399,057 | 839,870 |
| Number of posts with static images or video previews (visual posts) | 1,495,553 | 384,054 | 129,828 |
| Number of visual posts with available static images or video previews | 1,475,912 | 381,448 | 128,040 |
| Number of visual posts with available static images | 1,155,137 | 349,802 | 108,808 |
| Number of visual posts with available video previews | 321,258 | 31,661 | 19,249 |
| Number of posts without static images or video previews (only-text posts) | 6,295,935 | 1,015,003 | 710,042 |
| Number of available images | 1,563,373 | 466,082 | 160,972 |
| Number of available video previews | 322,442 | 31,665 | 19,249 |
| Number of posts with account information successfully retrieved | 5,125,240 | 1,383,842 | 815,218 |
| Number of visual posts with account information successfully retrieved | 1,465,276 | 379,012 | 127,293 |

and #StopAsianHate hashtags, respectively. We define tweets that contain at least one static image or a video as "visual posts." From the 2.0 million visual posts, we collected 2.2 million static images and 373,356 preview images of the videos.[1] We also collected the metadata for these posts, including the post likes and retweets, as of the time of data collection.

## Methods

### *Protest Phases*

To ensure consistent analysis of temporal features across all protests, we employed a consistent duration for the ignition phase for all protests, starting from the offset of the offline triggering event – the event that sparked a surge of attention and outrage. While there is a lack of clear rules in prior research for determining the length of this phase, with some indicating three days (LeFebvre & Armstrong, 2018), others suggesting one week (Eichstaedt et al., 2021), and some not specifying a specific time frame (Howard & Hussain, 2011), we defined the ignition phase through an empirical-driven approach. We first plotted the volume of tweets for three protests to observe the changes in volumes and found the triggering event for each protest, shown as the black lines. As the red line indicates, the triggering event is George Floyd's death on May 25, 2020 for BLM protest; Atlanta mass shooting on March 16, 2021 for SAH protest; and the inauguration of Donald Trump on January 20, 2017 for WM protest. As shown in Figure 1, the WM protest peaked for about seven days, while the discussions of BLM protest were still active until the one-month cutoff. The SAH protest had two consecutive peaks after the initial triggering event and died down after 15 days. Thus, we selected the maximum days — 30 days – to bind the ignition phase to analyze all protests as it covers multiple waves of heated online discussions across protests. We also present additional analyses using one week and 15 days as the universal ignition phase for all three protests in the Appendix D. We define the pre-ignition phase as the dates before the offline triggering event and the post-ignition phase as dates after the ignition phase.

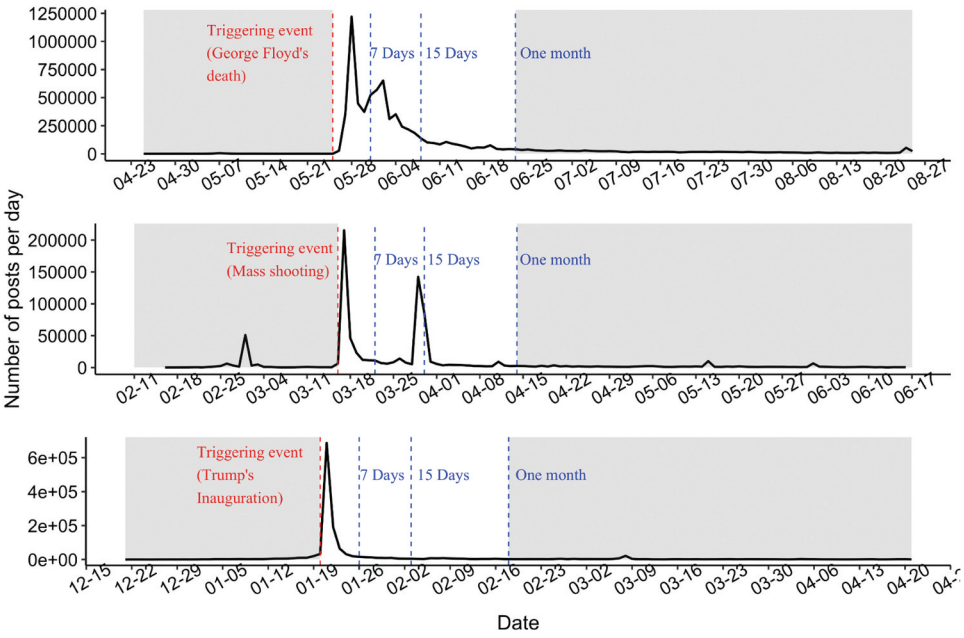


**Figure 1.** Number of movement-related posts by time (Top: BLM; Middle: SAH; Bottom: WM).

### *Unsupervised Learning on Visual Content Categories*

Unsupervised learning has been increasingly used in communication research to derive features of large-scale unlabeled data. Despite the prevalent use of unsupervised learning in analyzing text data like newspaper articles (Kaneko et al., 2021) and social media posts (Lu & Pan, 2021), fewer studies harness these methods in learning multimodal data. In fact, unsupervised learning techniques like clustering algorithms can effectively group images with similar objects into clusters, which can be used for deduplicating images (Steinert-Threlkeld et al., 2022) and discovering meaningful categories (Peng, Lu, et al., 2023b; Zhang & Peng, 2022). A rising body of research has been applying this method to different communication questions, such as deriving visual categories of politicians' online activities (Peng, 2021), establishing templates from millions of memes (Valensise et al., 2021), and classifying mobile activities by screenshots (Muise et al., 2022).

This paper extends the application of unsupervised learning to social mobilization research. Following Peng (2021) and Muise et al. (2022), we combined unsupervised machine learning and human validation to extract visual categories from static images and preview images of videos under each hashtag. We first extracted the features of each image into a feature array with 4,096 dimensions through transfer learning on the VGG16-hybrid1365 pre-trained Convolutional Neural Networks (B. Zhou et al., 2017). Given the scale of our data, we reduced the dimensionality of the feature vectors using principal component analysis and used factors that retained more than 80% of the variance for further analysis. Then, we used K-means clustering to cluster the images/video preview images under each hashtag into K clusters. Then, we derived the content categories and the optimal K for clustering results in two steps:

### Development of Content Categories

We first derived the *content categories* both theoretically and from observations. Theoretically, we are interested in three main visual features: crowds of protest, human presence, and photographs. Then, we drafted a codebook with content categories (crowd-protest photos, human photos, others) tested on the K = 30 solution of the static image datasets of all protests. For each cluster in each of the three solutions, we randomly sampled 20 static images and examined each image to see if it could fit into one of these categories. After that, we revised our codebook (see Appendix A) to include four mutually exclusive content categories (see Figure 2): (1) crowd-based protest photos (Panel A); (2) non-crowd-protest human photos (Panel B); (3) non-human photos (Panel C); and (4) non-photograph visuals (Panel D). Finally, we trained two research assistants with this codebook and achieved a 90.2% agreement (see Appendix B).

### Finding Optimal K

As the dataset of each protest contains a different number of pictures, the optimal K for each dataset may vary, requiring a comparison of results at different K values. Therefore, we ran the K-means clustering model on each of the six datasets (one static image dataset and one video preview dataset for each of the three protests), with K values set to 10, 15, 20, 25, 30, 35, and 40. The research assistants categorized the images for each K-means clustering solution based on these four categories. To determine the optimal K for each dataset, we calculated the cluster-wise consistency score within each solution by calculating the proportion of images in the dominant category in each cluster, and then averaged the consistency scores across clusters to obtain a solution-wise consistency score. We then

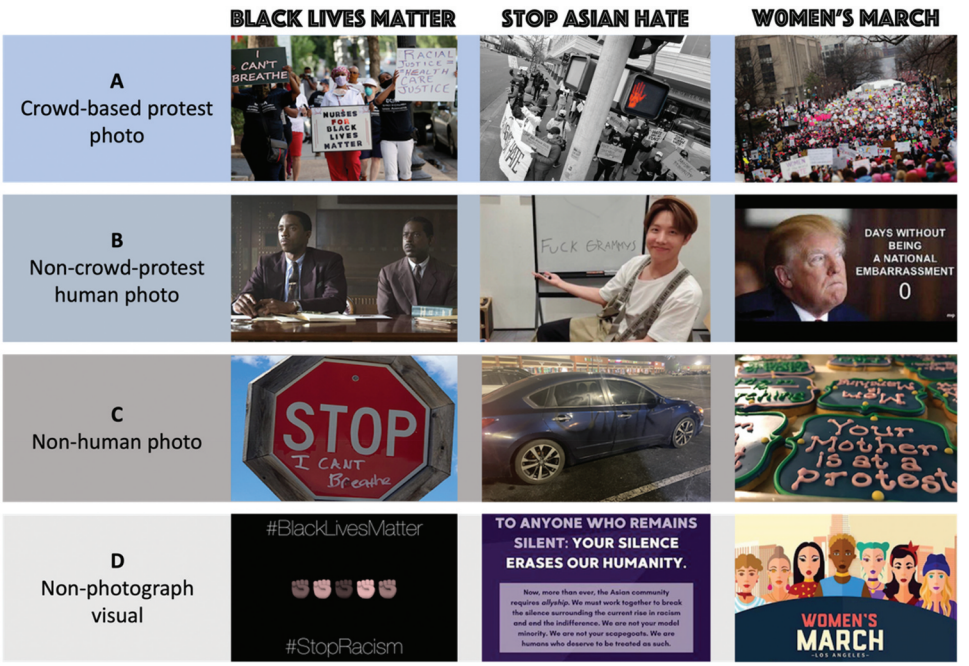


**Figure 2.** Content categories and examples.

selected the K value with the highest solution-wise consistency score (see Appendix B). Once the optimal K value was selected for each dataset, we coded each image in the same cluster as the same category, which formed the basis for further analysis of the visual categories.

### *Variable Coding and Regression Analysis*

To test H1 and H2, we used two dummy variables to denote whether a visual post contains a static image (1 = yes, 0 = no), and whether a visual post contains a video preview (1 = yes, 0 = no). Posts with only text become the reference category. We fitted a negative binomial regression to examine the relationship between the two visual dummy variables and the number of likes and retweets received by a post.

To test H3, based on our selected time window, we coded whether a post was made at the pre-ignition phase, ignition phase, or post-ignition phase into a categorical variable (with the ignition phase as baseline). We coded whether a post contains any visual content as a dummy variable (1 = yes, 0 = no). We then fitted a negative binomial regression with the categorical variable for temporality, the visual dummy variable, and their interaction terms on post likes and retweets. The baseline group of this two-way interaction would be the posts without visuals but created at the ignition phase. The robustness checks with different time windows (7 days and 15 days) are also provided in the supplemental material (see Appendix D).

To investigate RQ2 and RQ3, we focused our analysis on the visual posts, investigating the presence and effects of content categories. Thus, we coded whether each visual post contains a static image or a video preview that falls into each content category. For example, if a post contains a static image or a video preview showing a crowd-based protest scenario, we coded 1 for the "crowd-based protest" variable; otherwise, we coded it as 0. For RQ2b, we separated visual posts by modalities, while we combined them into visual posts but separated by stages to investigate RQ2c.

For RQ3, as we are comparing the association between different types of visual content categories and post engagement, we have posts with "non-photograph visuals" as the reference category, and see if posts with photograph-based visuals, in particular crowd-protest photos and human-based photos, can predict more post engagement. We then fitted a negative binomial regression with these categories as three dummy variables on post likes and retweets to explore the association between the use of different visual content categories and post likes and retweets.

For all regression analysis, we control the account followers and total number of posts each account made (with log transformation) in our main models. We also present the results without the controls in Appendix C.

## Results

### *General Superior Effects of Images and Videos*

H1 and H2 hypothesize that posts with static images and videos have higher engagement than text posts. As Table 2 shows, for all three protests, containing images predicts more likes ($\beta_{BLM} = 1.463$, $p < .001$; $\beta_{SAH} = 1.951$, $p < .001$; $\beta_{WM} = 1.340$, $p < .001$) and retweets ($\beta_{BLM} = 1.777$, $p < .001$; $\beta_{SAH} = 2.671$, $p < .001$; $\beta_{WM} = 1.612$, $p < .001$). Similarly, the inclusion of video has positive and statistically significant effects on both post likes ($\beta_{BLM} =$

2.440, $p < .001$; $\beta_{SAH} = 2.230$, $p < .001$; $\beta_{WM} = 1.765$, $p < .001$) and retweets ($\beta_{BLM} = 2.865$, $p < .001$; $\beta_{SAH} = 3.084$, $p < .001$; $\beta_{WM} = 2.221$, $p < .001$) for all three protests. H1 and H2 were supported.

Regarding RQ1, we found that posts with videos predict slightly more likes and retweets than posts with static images for all three protests. This suggests that videos can be more powerful in eliciting post engagement than static images.

### The Role of Visuals Across Protest Stages

H3 hypothesizes that visuals have greater effects on audience engagement during the ignition phase of a social-mediated protest. We provided statistical tests for the interaction effects specified in H3 in Table 3 and visualized the results in Appendix D. Posts with visuals created at the ignition phase predict the most likes and retweets for WM protest among all six conditions. For the SAH protest, the positive effect of visuals on retweets is more pronounced during the ignition phase than during the other two phases, but the positive effect of visuals on likes is more pronounced during the pre-ignition phase than during the ignition phase. Results when using different time windows are presented in Appendix D (See Table D1 and Table D2 in Appendix D). The results are robust with 15 days as the ignition phase but less robust with 7 days as the ignition phase. In a word, H3 was partially supported.

### Content Categories of Protest Visuals

RQ2 asks what kind of visuals are circulated in protest posts on social media. Figure 3 illustrates the prevalence of our content categories. We did not observe a dominance of one content category across protests. Rather, we saw clear differences in visual content in these three protests. Photographs dominated the visual WM posts, with 69.3% containing crowd-based protest photos, 9.5% containing human photos that did not show crowds, and 7.6% containing non-human photos. In comparison, 17.0% of visual posts contained non-photograph visuals, such as cartoons and illustrations. Photos also dominated visuals in BLM posts, but in different ways. 33.8% contained photographs of people not in protest crowds, including images of George Floyd pinned to the ground by the police, while 21.9%

**Table 2.** Visual predictors of audience engagement.

| | Post likes | | | Post retweets | | |
|---|---|---|---|---|---|---|
| | BLM | SAH | WM | BLM | SAH | WM |
| Has Image | 1.463*** | 1.951*** | 1.340*** | 1.777*** | 2.671*** | 1.612*** |
| | (0.003) | (0.008) | (0.004) | (0.004) | (0.013) | (0.006) |
| Has Video | 2.440*** | 2.230*** | 1.765*** | 2.865*** | 3.084*** | 2.221*** |
| | (0.004) | (0.018) | (0.012) | (0.006) | (0.027) | (0.016) |
| Account followers (log) | 0.663*** | 0.645*** | 0.670*** | 0.634*** | 0.464*** | 0.722*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Account posts (log) | −0.289*** | −0.234*** | −0.300*** | −0.189*** | 0.123*** | −0.259*** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Constant | −0.611*** | −1.020*** | −1.013*** | −2.540*** | −3.712*** | −2.883*** |
| | (0.005) | (0.013) | (0.010) | (0.008) | (0.019) | (0.014) |
| Observations | 5,125,240 | 815,218 | 1,383,842 | 5,125,240 | 815,218 | 1,383,842 |

Notes: ***$p$ <0.001.

**Table 3.** Visual and phase predictors of audience engagement.

| | Post likes | | | Post retweets | | |
|---|---|---|---|---|---|---|
| | BLM | SAH | WM | BLM | SAH | WM |
| Has visual | 1.826*** | 2.031*** | 1.436*** | 2.173*** | 2.651*** | 1.720*** |
| | (0.003) | (0.009) | (0.004) | (0.004) | (0.013) | (0.006) |
| Pre-ignition | −0.130*** | −0.376*** | −0.088*** | −0.268*** | −0.275*** | −0.023. |
| | (0.020) | (0.010) | (0.009) | (0.028) | (0.016) | (0.012) |
| Post-ignition | −0.267*** | 0.388*** | 0.067*** | −0.207*** | 1.281*** | −0.118*** |
| | (0.004) | (0.011) | (0.008) | (0.005) | (0.016) | (0.011) |
| Has visual X pre-ignition | 0.221*** | 0.367*** | −0.487*** | 1.126*** | −0.144** | −0.577*** |
| | (0.035) | (0.032) | (0.019) | (0.048) | (0.048) | (0.026) |
| Has visual X post-ignition | −0.428*** | −0.469*** | −1.011*** | −0.361*** | −0.086** | −0.805*** |
| | (0.006) | (0.020) | (0.017) | (0.009) | (0.030) | (0.024) |
| Account followers (log) | 0.668*** | 0.647*** | 0.674*** | 0.636*** | 0.510*** | 0.726*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Account posts (log) | −0.290*** | −0.233*** | −0.302*** | −0.185*** | 0.116*** | −0.263*** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| Constant | −0.600*** | −1.052*** | −1.018*** | −2.557*** | −4.127*** | −2.862*** |
| | (0.005) | (0.013) | (0.010) | (0.008) | (0.020) | (0.014) |
| Observation | 5,125,240 | 815,218 | 1,383,842 | 5,125,240 | 815,218 | 1,383,842 |

Notes: *$p$ <0.05; **$p$ <0.01; ***$p$ <0.001.

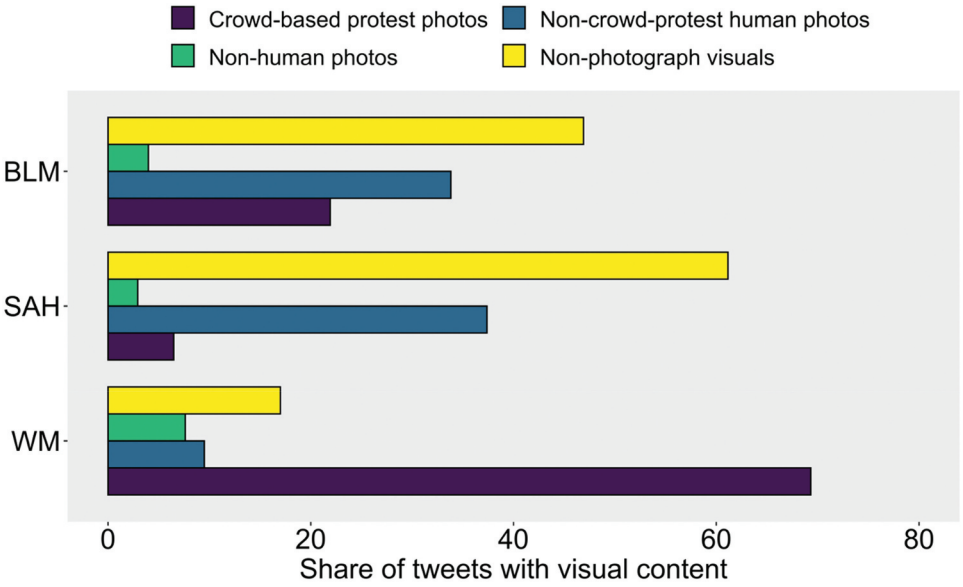


**Figure 3.** Content categories of visual posts by movements.

of visual posts contained crowd-based photos. Photos of non-human objects or landscapes comprised 4.0% of visual BLM posts. The remaining 46.9% of visual posts used illustrations or other non-photograph visuals to promote BLM-related messages. The most salient category in SAH was non-photograph visual, appearing in 61.2% of visual posts. Another 37.4% of visual posts contained human photos not in a crowd setting, 6.5% contained images with crowd protests, and 2.9% contained non-human photographs.

One step further, we found similarities and heterogeneities in visual content across modalities, temporalities, and protests. As shown in Figure 4, for posts on BLM and SAH

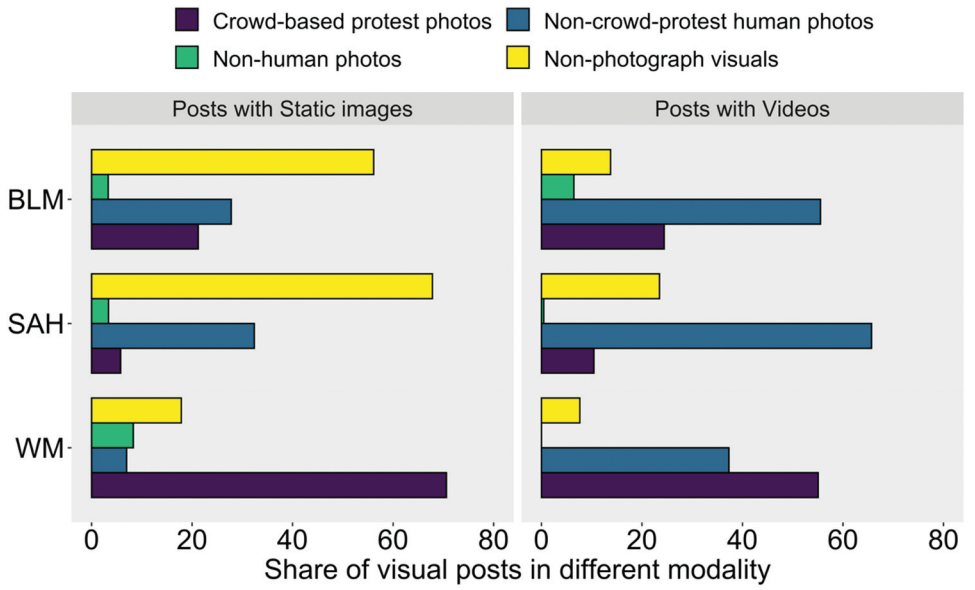


**Figure 4.** Content categories of visual posts in different modalities.

protests, non-photograph visuals occupied 56.1% and 67.8% of posts with static images, while human photos that did not depict crowd protests dominated posts with videos (55.5% and 65.7%). By contrast, crowd-based protest photos dominated the visuals of static image posts and video posts for the WM protest. Temporal features showed greater similarity between BLM and WM with SAH being the outlier. As Figure 5 highlights, there was a higher level of crowd-based protest photos during the ignition phase compared to other phases for the BLM and WM protests while non-photograph visuals dominated the visual posts at all phases for the SAH protest.

### *Effects of Visual Categories on Audience Engagement*

RQ3 asks how different visual categories may predict audience engagement. As shown in Table 4, compared to posts with non-photograph visuals as the reference category, we found that visual posts with crowd-based photos had a positive and statistically significant effect on likes ($\beta_{BLM} = 1.145$, $p < .001$; $\beta_{SAH} = 0.381$, $p < .001$; $\beta_{WM} = 0.928$, $p < .001$) and retweets ($\beta_{BLM} = 1.087$, $p < 0.001$; $\beta_{SAH} = 0.772$, $p < .001$; $\beta_{WM} = 0.738$, $p < .001$) across the three protests. Visual posts with non-crowd-protest human photographs had a positive and significant effect on likes ($\beta_{BLM} = 1.001$, $p < .001$; $\beta_{SAH} = 0.683$, $p < .001$; $\beta_{WM} = 0.337$, $p < .001$) and retweets ($\beta_{BLM} = 1.105$, $p < .001$; $\beta_{SAH} = 0.948$, $p < .001$; $\beta_{WM} = 0.298$, $p < .001$) for all three protests. Posts containing non-human photographs also had statistically significant associations with post retweets for the three campaigns ($\beta_{BLM} = 0.487$, $p < .001$; $\beta_{SAH} = 0.838$, $p < .001$; $\beta_{WM} = 0.043$, $p < .05$). However, the same positive association on likes only occurred among BLM posts ($\beta_{BLM} = 0.607$, $p < .001$) and WM protest ($\beta_{WM} = 0.402$, $p < .001$), while there was a negative association with retweets of posts on the SAH protest ($\beta_{SAH} = -0.164$, $p < .001$).

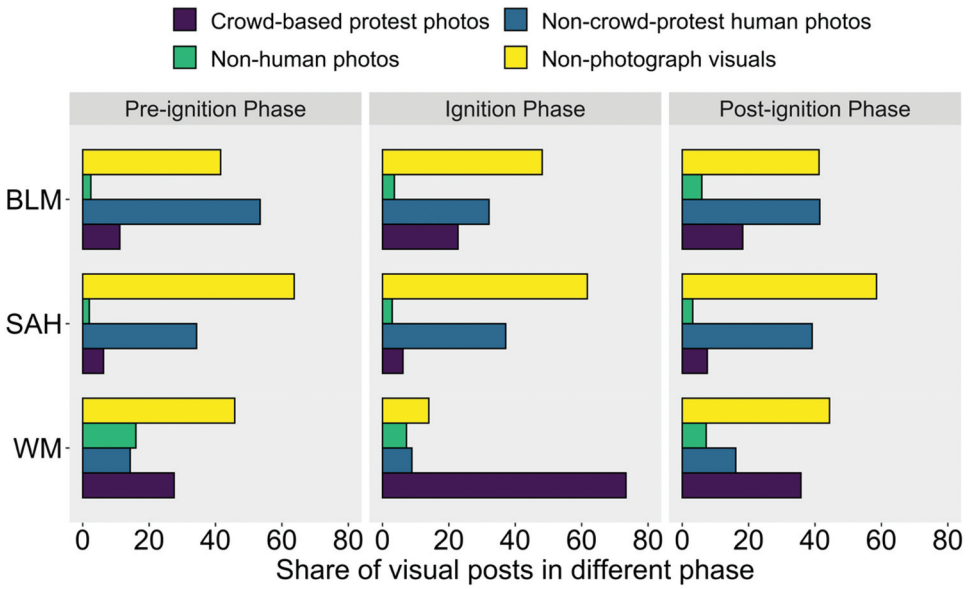


**Figure 5.** Content categories of visual posts in different phases.

**Table 4.** Content category predictors of audience engagement.

| | Post likes | | | Post retweets | | |
|---|---|---|---|---|---|---|
| | BLM | SAH | WM | BLM | SAH | WM |
| Crowd-based protest photo | 1.145*** (0.005) | 0.381*** (0.026) | 0.928*** (0.009) | 1.087*** (0.006) | 0.772*** (0.037) | 0.738*** (0.012) |
| Non-crowd-protest human photo | 1.001*** (0.004) | 0.683*** (0.013) | 0.337*** (0.014) | 1.105*** (0.006) | 0.948*** (0.020) | 0.298*** (0.018) |
| Non-human photo | 0.607*** (0.010) | −0.164*** (0.038) | 0.402*** (0.015) | 0.487*** (0.013) | 0.838*** (0.054) | 0.043* (0.019) |
| Account followers (log) | 0.574*** (0.001) | 0.488*** (0.002) | 0.727*** (0.002) | 0.497*** (0.001) | 0.320*** (0.003) | 0.733*** (0.003) |
| Account posts (log) | −0.229*** (0.001) | −0.073*** (0.003) | −0.283*** (0.002) | −0.132*** (0.001) | 0.217*** (0.005) | −0.219*** (0.003) |
| Constant | 0.440*** (0.008) | 0.133*** (0.024) | −0.947*** (0.019) | −0.854*** (0.011) | −1.584*** (0.034) | −2.242*** (0.025) |
| Observations | 1,465,276 | 127,293 | 379,012 | 1,465,276 | 127,293 | 379,012 |

Notes: *$p$ <0.05; **$p$ <0.01; ***$p$ <0.001

## *Qualitative Analysis and Interpretation*

To further explore the content and strategies of these different content categories and their association with post engagement, we sampled the 50 most-engaged posts within each stage (pre-ignition, ignition, and post-ignition) for each protest for qualitative reading.[2] For each visual post, we followed grounded theory (Creswell & Poth, 2016) by applying open coding to its visuals, and then formed our theory by shaping conceptual labels and categories from our coding results.

Consistent with our regression analysis, the portrayals of crowds are salient among the most-engaged posts during the ignition phase for all protests. Most of the crowd-based visuals involve large-scale street demonstrations, occurring in nearly 88% of WM posts, 32%

of BLM posts, and 18% of SAH posts during the ignition phase. However, as Figure 6 shows, while street demonstration visuals of BLM and SAH protests usually portray grievances (Panel A1), WM street demonstrations are more likely to portray a proud or peaceful crowd (Panel A2), calling for solidarity and international coalition.

Many BLM and SAH protest visuals portrayed victims but not WM visuals. Most were human photographs that were not part of street demonstrations, as Panel B in Figure 6 shows. More than 53% of BLM posts during the ignition phase portrayed victims and the percentage rose to 64% during the post-ignition phase. The percentage of portraying victims went from 18% to 81% from the ignition phase to the post-ignition phase for SAH posts. Victim portrayal takes several forms, including personal photos (e.g., Panel B1 of Figure 6) and family photos. Violence is accompanied by some victim portrayals. For example, more than 50% of BLM visuals during the ignition phase portrayed police brutality or street violence toward minority victims, such as Panel B2 in Figure 6. For both BLM and SAH, the victims portrayed were not necessarily those whose murders had been the key triggering events, George Floyd and those who died in the Atlanta mass shooting. For example, the SAH protest visuals addressed racist events such as the death of Instagram Star Cat Ponzu, Serbian volleyball players' anti-Asian racist behaviors, and the unprovoked attack on an Asian female in New York. More of the SAH posts were unique popular posts than BLM and MW posts. In line with our categorization findings, non-photograph visuals were prevalent among the most-engaged images. Many of these non-photograph visuals were crafted posters with information about anti-Asian accidents and clear appeals to participation (Panel C1). Some of them are even simpler with only one or several lines of slogans. Another interesting finding is the salience of K-pop celebrities across protest stages. Nearly


**Figure 6.** Visual examples from qualitative findings.

43% of SAH visual posts during the ignition phase involve BTS, the world-famous K-pop group, and their endeavors in anti-Asian-hate activities. An example can be seen in Panel C2 in Figure 6, showing BTS's Kim Nam Jun (RM) delivering remarks at the UN General Assembly and calling for self-love and equality. Some posts also share more casual BTS visuals about their performances, life, or controversies, without a clear linkage to the SAH goal.

## Discussion

If a picture is worth a thousand words, what roles can we expect visuals to have in mobilizing social-mediated protests? This paper advances our understanding of this question by analyzing about ten million social media posts collected from three social-mediated protests: BLM, SAH, and WM. We observe the superior effects of static images and videos on attracting audience engagement in general compared to text posts. This study is one of the early investigations into the role of visual media across different stages of social-mediated protests, showing the superior effects of visuals are more pronounced during the ignition phase of the protest, compared with the phases before and after. By applying unsupervised image clustering on protest visuals circulated on social media, we systematically establish four common visual content categories – crowd-based photos, non-crowd-protest human photos, non-human photos, and non-photograph visuals – and their presence across protests. Furthermore, we explore how each visual category predicts post engagement and find heterogeneous effects across content categories and protests through both regression and qualitative analyses. We discuss the implications and limitations of our study below.

### *The Role of Visuals from Both General and Temporality Perspectives*

This study has made several theoretical contributions to our understanding of the effects of visual communication. First, our results reveal the superior effects of visual media on online engagement with protest messages compared to text messages. We join an emerging literature of visual politics that studies the impact of visuals on different metrics of political participation (Horiuchi et al., 2012; Lilleker & Veneti, 2023; Ryan, 2012) and expand it to a social protest context. As participants in social-mediated protests can easily document crises and protests through personal expressions with visuals, these visuals can in turn have significant effects in attracting more potential allies to the protests and then shaping more long-lasting movements.

We also contribute to the current understanding of visual effects by distinguishing between static images and videos to understand how they mobilize audience engagement. As prior research suggests that videos elicit more credibility judgments as they can cue more realism heuristics than text or single-modality images, we find that posts with videos are more engaging than those with static images for social-mediated protests. As there have been limited studies comparing the differences between visual modalities in the context of social protests, we call for more systematic tests on the mechanisms and conditions of how these different types of visuals engage online audiences across protests. Given that the use of social media is shifting toward more video-based platforms like TikTok and YouTube, this line of research can also have practical implications for social protestors to broadcast their

messages and for audiences to understand online political participation embedded in new visual forms.

Despite the superiority of visual effects in general, this study highlights important contingencies and limitations of visual media effects on social protests from a temporality perspective. Hellmeier et al. (2018) document a "sequential protest effect" in which the effects of prominent protest events on subsequent media attention become weaker soon after the end of the event. In our paper, we tested this effect systematically by dividing protest discussions into three phases, pre-ignition, ignition, and post-ignition phases based on prior literature, and found that the effect of visual media peaks in the ignition phase of the protest by attracting more retweets than the nonvisual and visual media created before and after the ignition phases. The more nuanced findings in the prediction of likes also suggest that the same content can prompt different engagement behaviors in different ways (Molina et al., 2022; Tenenboim & Cohen, 2015).

### *The Differential Effects of Visual Content Categories in Social Protest Visuals*

In addition, this study reveals the differential effects of visual content categories on audience engagement, going beyond a simple comparison of modalities (e.g., visuals versus texts) to explore the effects of different types of visuals. Specifically, we find that photographs featuring crowds are particularly successful in attracting audience engagement. The salient presence of a street demonstration among the most-engaged visuals of all three protests aligns with prior research findings that crowd portrayals may lead to greater audience engagement (Rössler et al., 2011) and the portrayal of the crowds occupying Taksim Square won the most retweets (Ozduzen & McGarry, 2020). Different features of crowds in BLM/SAH protest visuals versus WM protest visuals call for research on the mechanisms of the success of crowd portrayals.

Our results also show that photographs, especially human-based photographs, perform better than other non-photograph visuals in attracting likes to the visual posts. As Sundar and Limperos (2013) explain in the modality-based gratifications, the "realism heuristics" from photographs may motivate individuals to perceive the transmitted content as more real than that communicated in text form. Our finding also extends the photograph-engaging effects found by Li and Xie (2020) in digital advertising to political communication. Furthermore, the finding that the presence of humans is associated with more engagement supplements existing works in political and science communication (Lu & Shen, 2023; Peng, 2021). In particular, our qualitative findings that victims and violence are prevalent among the most-engaged visuals provide evidence of why the presence of humans affects visual engagement in a political protest context. Sharing photographic images on social media can also potentially "draw communities together around shared events, contexts, and ideals" (Oeldorf-Hirsch & Sundar, 2016). Therefore, we call for more research with causality-based designs to examine the role of humans and photographs in mobilizing social movements.

### *Understanding the Roles of Visual-Supportive Digital Media in Social Movements*

The findings of our study also contribute to a multifaceted understanding of the roles that digital media play in mobilizing social movements. Visual-supportive digital technologies, particularly easily accessible camera phones, apps, and visual-oriented social media

platforms, have triggered the rise of "contemporary visual activism," which takes various forms, including "citizen camera witnessing to vlogging, selfie activism, and political meme culture" (Jenzen et al., 2021). As video-sharing social media like TikTok have made it easier to post visuals and propagate these visuals to international audiences, it is worth discussing whether visual-based messages may provide effective framings to legitimate and propagate the protests. While social movement literature broadly explains the affordances of digital media in mobilizing online and offline protests by reducing costs and increasing connectivity (Bennett & Segerberg, 2012; Earl & Kimport, 2011), the interaction between the visuality of digital media and social protests or social movements remains an unexplored yet crucial research topic for future social movement scholarship.

Our findings also suggest that the role of visual media is diverse across social protests, providing a comparative perspective in light of the relationship between technology and society. Among the three protests we tested, the SAH protest yields more deviant results than the other two protests. For example, while photographs dominate online visual portrayals of BLM and WM, non-photograph visuals that contain educational facts and spreadable messages for engagement make up the majority of visual representations of SAH on Twitter. Meanwhile, as Tong et al. (2022) found by comparing textual posts, BLM posts focus on accusing police brutality while the SAH discourses center on racism toward the Asian community since COVID-19 and cover more topics than BLM. Our finding of the salient presence of BTS-related visuals in SAH posts echoes this finding. It also implies that concurrent events with similar topic linkage but different purposes may influence the discussion of a particular social-mediated protest. Posts under SAH hashtags that only address BTS also call for more research on those who posted protest visuals and their intentions. Thus, to make sense of visual effects across protests and social movements, more studies need to investigate how different contexts, locus of problems, participants, and offline manifestations may lead to different visual representations across different protests and their engagement.

Our results also contribute to theoretical understanding of contemporary activism against social inequalities. These three protests may represent a broader social trend, and their findings elucidate the nature of online discussions about movements against racism, sexism, and social injustices, which are critical areas of study for scholars and activists alike. Visual media is a powerful tool for activists to bring attention to severe violations of social justice, hold actors who did harm accountable, and amplify the voices of citizens to produce counternarratives that disrupt traditional media routines (Bock, 2016). Ordinary people's ability to see and witness is itself a form of power that has the potential to hold state actors in check (Bock, 2016). This study resonates with this perspective and documents the effective power of visual media in mobilizing the public and generating heightened attention to the prevalence of systematic racism and sexism in society. The temporal findings in our research suggest the importance of the timing for broadcasting protest messages, which can help inform the development of effective communication strategies for contemporary social protests and movements. However, the power of visual media has its limits. Its shock value and emotional impact do not sustain for a long time, and calls for social justice often rely on isolated incidents and do not sustain constant, long-form public attention. The question of how to integrate the pursuit of equity and fairness into everyday social media discussions and convert them into actual far-reaching policy and societal changes remains open and needs further reflection. The differential effects of visual content categories can also help social movement activists make more informed decisions about the types of visual posts they create and share on social media platforms.

### *Limitations and Future Research*

This study has several limitations. First, our investigation focuses on one platform: Twitter. Given recent changes to the platform, it remains to be seen what role Twitter (now as "X") will play in the future. Other platforms like Instagram (Cornet et al., 2017) and TikTok (Hautea et al., 2021) also play important roles in the mobilization of social movements. It remains to be empirically tested whether the features and roles of visuals in social movements are similar across platforms, or whether they vary due to the different user characteristics, social norms, and technological affordances associated with each platform. Social movements on Instagram use some of the same visual categories as Twitter, such as photographs, infographics, and artwork (Cornet et al., 2017). However, as Instagram does not facilitate resharing content like Twitter does, users have to resort to third-party applications to retransmit visual content. Future research could replicate our analysis with data from other platforms to explore the similar or different roles of visuals on the engagement of protests and movements.

Our data and analysis also contain location-related limitations. First, since only a very small proportion of tweets in our corpus contain location information (3.6% of BLM posts, 1.7% of SAH posts, and 8.5% of WM posts), we are unable to investigate how users in different locations create and engage visual media. Additionally, since the three protests were triggered by offline events in the United States and English language posts dominate our data, the effects of visual media we found may be different in other cultural or political contexts. For example, Zhang and Peng (2022) analyzed protest-related visuals on Weibo, a Chinese social media platform, and discovered that many of the images were photographs of handwritten petition letters, a content category rarely seen in the protests we examined. Future studies should explore how visuals function similarly or differently in social protests and movements and across cultural contexts from a comparative perspective. For instance, research on the visualization of the Gezi protests in Turkey also revealed that illustrations of martyrs gained many retweets.

Methodologically, our paper is not able to establish a definitive causality relationship between visual-sharing activities and the engagement with protests. For example, we were unable to isolate the potential impact of mainstream media on protest attention and engagement. However, for future research in this area, our research has methodological implications. The application of deep learning and unsupervised clustering methods on millions of protest visuals in this paper contributes methodologically to social movement studies in political communication. This image-as-data approach (Joo & Steinert-Threlkeld, 2022) provides an alternative approach to studying social movements from multimodal unstructured protest data. The analytical framework that combines unsupervised machine learning and human-based validation on images can be extended to many areas in political communication such as multimodal misinformation or media coverage of politicians (Peng, Lu, et al., 2023b).

## Notes

1. The number of visuals is larger than the number of posts as more than 304 thousand tweets contained either multiple images or multiple videos. As we retrospectively retrieved account information and encountered a sudden shift in the Twitter Academic API, which resulted in our inability to retrieve all users' metadata, we included posts with successfully downloaded account information in our analysis.

2. We calculated the post engagement by adding up the post likes, comments, and retweets and then normalized by the number of followers of the poster.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Notes on contributors

***Yingdan Lu*** (PhD, Stanford University) is an Assistant Professor of Communication Studies at Northwestern University. Her research focuses on digital technology, political communication, and information manipulation in authoritarian and democratic contexts. Her work has appeared in peer-reviewed journals such as Political Communication, New Media & Society, Human-Computer Interaction, Computational Communication Research, and among other peer-reviewed journals. For more information, see her website: https://yingdanlu.com/

***Yilang Peng*** (PhD, Annenberg School for Communication, University of Pennsylvania) is an assistant professor in the Department of Financial Planning, Housing and Consumer Economics at the University of Georgia. His scholarship is at the intersection of computational social science, visual communication, science communication, and social media. His research uses computer vision methods to investigate the production and effects of visual messages across different communication contexts.

## ORCID

Yingdan Lu http://orcid.org/0000-0002-9955-6070
Yilang Peng http://orcid.org/0000-0001-7711-9518

## References

Aldous, K. K., An, J. & Jansen, B. J. (2019, July). View, like, comment, post: Analyzing user engagement by topic at 4 levels across 5 social media platforms for 53 news organizations. In Proceedings of the International AAAI Conference on Web and Social Media (Vol. 13, pp. 47–57).

Allen, O. M., Chen, E., & Ferrara, E. (2021, October). Pictures as a form of protest: A survey and analysis of images posted during the stop Asian hate movement on Twitter. In *2021 IEEE 18th international conference on mobile ad hoc and smart systems MASS*, (pp. 667–668). IEEE.

Andén-Papadopoulos, K. (2014). Citizen camera-witnessing: Embodied political dissent in the age of 'mediated mass self-communication'. *New Media & Society*, *16*(5), 753–769. https://doi.org/10.1177/1461444813489863

Anderson, M., Barthel, M., Perrin, A., & Vogels, E. A. (2020 , June 10). *#blacklivesmatter surges on twitter after George Floyd's death*. Pew Research Center. Retrieved June 1, 2022, https://www.pewresearch.org/fact-tank/2020/06/10/blacklivesmatter-surges-on-twitter-after-george-floyds-death/

Arpan, L. M., Baker, K., Lee, Y., Jung, T., Lorusso, L., & Smith, J. (2006). News coverage of social protests and the effects of photographs and prior attitudes. *Mass Communication & Society*, *9*(1), 1–20. https://doi.org/10.1207/s15327825mcs0901_1

Bakhshi, S., Shamma, D. A., & Gilbert, E. (2014, April). 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*. Toronto, Canada, (pp. 965–974).

Barry, A. M. S. (1997). *Visual intelligence: Perception, image, and manipulation in visual communication*. SUNY Press.

Bayerl, P. S., & Stoynov, L. (2016). Revenge by photoshop: Memefying police acts in the public dialogue about injustice. *New Media & Society*, *18*(6), 1006–1026. https://doi.org/10.1177/1461444814554747

Baylor, T. (1996). Media framing of movement protest: The case of American Indian protest. *The Social Science Journal*, *33*(3), 241–255. https://doi.org/10.1016/S0362-3319(96)90021-X

Bennett, W. L., & Segerberg, A. (2012). The logic of connective action: Digital media and the personalization of contentious politics. *Information, Communication & Society*, *15*(5), 739–768. https://doi.org/10.1080/1369118X.2012.670661

Benski, T., Langman, L., Perugorría, I. & Tejerina, B. (2013). From the streets and squares to social movement studies: What have we learned?. *Current Sociology*, *61*(4), 541–561.

Bock, M. A. (2016). Film the police! Cop-watching and its embodied narratives. *Journal of Communication*, *66*(1), 13–34. https://doi.org/10.1111/jcom.12204

Brader, T. (2005). Striking a responsive chord: How political ads motivate and persuade voters by appealing to emotions. *American Journal of Political Science*, *49*(2), 388–405. https://doi.org/10.1111/j.0092-5853.2005.00130.x

Brown, D. K. (2022). Media models for nonviolence: Instagram representations of the #WomensMarch mass mobilization news and audience engagement. *International Journal of Communication*, *16*, 1669–1687, Article 19.

Brown, D. K. & Mourão, R. R. (2021). Protest coverage matters: How media framing and visual communication affects support for black civil rights protests. *Mass Communication & Society*, *24*(4), 576–596.

Bruni, L., Francalanci, C., & Giacomazzi, P. (2012). The role of multimedia content in determining the virality of social media information. *Information*, *3*(3), 278–289. https://doi.org/10.3390/info3030278

Casas, A., & Williams, N. W. (2019). Images that matter: Online protests and the mobilizing role of pictures. *Political Research Quarterly*, *72*(2), 360–375. https://doi.org/10.1177/1065912918786805

Clothey, R. A., Koku, E. F., Erkin, E., & Emat, H. (2016). A voice for the voiceless: Online social activism in Uyghur language blogs and state control of the internet in China. *Information, Communication & Society*, *19*(6), 858–874. https://doi.org/10.1080/1369118x.2015.1061577

Cornet, V. P., Hall, N. K., Cafaro, F., & Brady, E. L. (2017, May). How image-based social media websites support social movements. In *Proceedings of the 2017 CHI conference extended abstracts on human factors in computing systems*. Denver, CO, (pp. 2473–2479).

Corrigall-Brown, C., & Wilkes, R. (2012). Picturing protest: The visual framing of collective action by first Nations in Canada. *American Behavioral Scientist*, *56*(2), 223–243. https://doi.org/10.1177/0002764211419357

Creswell, J. W., & Poth, C. N. (2016). *Qualitative inquiry and research design: Choosing among five approaches*. Sage publications.

Della Porta, D., & Mattoni, A. (2014). Social networking sites in pro-democracy and anti-austerity protests: Some thoughts from a social movement perspective. Trottier, Daniel& Fuchs, Christian eds. In *Social media, politics and the state* (pp. 39–63). New York, NY: Routledge.

Earl, J., Hunt, J., Garrett, R. K., & Dal, A. (2015). New technologies and social movements Della Porta, Donatella & Diani, Mario eds. In *The oxford handbook of social movements* (pp. 355–366). Oxford University Press.

Earl, J., & Kimport, K. (2011). *Digitally enabled social change: Activism in the internet age*. MIT Press.

Earl, J., McKee Hurwitz, H., Mejia Mesinas, A., Tolan, M., & Arlotti, A. (2013). This protest will be tweeted: Twitter and protest policing during the Pittsburgh G20. *Information, Communication & Society*, *16*(4), 459–478. https://doi.org/10.1080/1369118X.2013.777756

Eichstaedt, J. C., Sherman, G. T., Giorgi, S., Roberts, S. O., Reynolds, M. E., Ungar, L. H., & Guntuku, S. C. (2021). The emotional and mental health impact of the murder of George Floyd on the US population. *Proceedings of the National Academy of Sciences*, *118*(39), e2109139118. https://doi.org/10.1073/pnas.2109139118

Fan, L., Yu, H., & Gilliland, A. J. (2021). # StopAsianHate: Archiving and analyzing twitter discourse in the wake of the 2021 Atlanta spa shootings. *Proceedings of the Association for Information Science and Technology*, *58*(1), 440–444. https://doi.org/10.1002/pra2.475

Garrett, R. K. (2006). Protest in an information society: A review of literature on social movements and new ICTs. *Information, Communication & Society* [Retrieved from], *9*(2), 202–224. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2129853

Geise, S., Heck, A., & Panke, D. (2021). The effects of digital media images on political participation online: Results of an eye-tracking experiment integrating individual perceptions of "photo news factors". *Policy & Internet*, *13*(1), 54–85. https://doi.org/10.1002/poi3.235

Geise, S., Panke, D., & Heck, A. (2021). Still images—moving people? How media images of protest issues and movements influence participatory intentions. *The International Journal of Press/politics*, *26*(1), 92–118. https://doi.org/10.1177/1940161220968534

Gerlitz, C., & Helmond, A. (2013). The like economy: Social buttons and the data-intensive web. *New Media & Society*, *15*(8), 1348–1365. https://doi.org/10.1177/1461444812472322

González-Bailón, S., Borge-Holthoefer, J., Rivero, A., & Moreno, Y. (2011). The dynamics of protest recruitment through an online network. *Scientific Reports*, *1*(1), 1–7. https://doi.org/10.1038/srep00197

Grabe, M. E., & Bucy, E. P. (2009). *Image bite politics: News and the visual framing of elections*. Oxford University Press.

Hall, S., Lenette, C., Murray, S., Chan, C., Flannery, A., & Vickery, K. (2018). #letthemstay: Visual representations of protests and community mobilization for asylum seekers in Australia. *Journal of Critical Thought and Praxis*, *7*(1). https://doi.org/10.31274/jctp-180810-105

Hameleers, M., Powell, T. E., Van Der Meer, T. G., & Bos, L. (2020). A picture paints a thousand lies? The effects and mechanisms of multimodal disinformation and rebuttals disseminated via social media. *Political Communication*, *37*(2), 281–301. https://doi.org/10.1080/10584609.2019.1674979

Hautea, S., Parks, P., Takahashi, B., & Zeng, J. (2021). Showing they care (or don't): Affective publics and ambivalent climate activism on TikTok. *Social Media+ Society*, *7*(2), 20563051211012344. https://doi.org/10.1177/20563051211012344

Hellmeier, S., Weidmann, N. B. & Geelmuyden Rød, E. (2018). In the spotlight: Analyzing sequential attention effects in protest reporting. *Political Communication*, *35*(4), 587–611.

Horiuchi, Y., Komatsu, T., & Nakaya, F. (2012). Should candidates smile to win elections? An application of automated face recognition technology. *Political Psychology*, *33*(6), 925–933. https://doi.org/10.1111/j.1467-9221.2012.00917.x

Howard, P. N., Duffy, A., Freelon, D., Hussain, M. M., Mari, W., & Maziad, M. (2011). Opening closed regimes: What was the role of social media during the Arab Spring? https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2595096

Howard, P. N., & Hussain, M. M. (2011). The upheavals in Egypt and Tunisia: The role of digital media. *Journal of Democracy*, *22*(3), 35–48. https://doi.org/10.1353/jod.2011.0041

Jenzen, O., Erhart, I., Eslen-Ziya, H., Korkut, U. & McGarry, A. (2021). The symbol of social media in contemporary protest. *Twitter and the Gezi Park Movement. Convergence*, *27*(2), 414–437.

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). https://doi.org/10.5117/CCR2022.1.001.JOO

Jost, J. T., Barberá, P., Bonneau, R., Langer, M., Metzger, M., Nagler, J., Sterling, J., & Tucker, J. A. (2018). How social media facilitates political protest: Information, motivation, and social networks. *Political Psychology*, *39*(S1), 85–118. https://doi.org/10.1111/pops.12478

Kaneko, T., Asano, T. A., & Miwa, H. (2021). Estimating ideal points of newspapers from editorial texts. *The International Journal of Press/politics*, *26*(3), 719–742. https://doi.org/10.1177/1940161220935058

Kim, J. W. (2018). They liked and shared: Effects of social media virality metrics on perceptions of message influence and behavioral intentions. *Computers in Human Behavior*, *84*, 153–161. https://doi.org/10.1016/j.chb.2018.01.030

Koopmans, R. (2004). Protest in time and space: The evolution of waves of contention. In D. A. Snow, S. A. Soule, & H. Kriesi (Eds.), *The Blackwell companion to social movements* (pp. 19–46). Wiley-Blackwell.

Lee, F. L., & Chan, J. M. (2018). *Media and protest logics in the digital era: The umbrella movement in Hong Kong*. Oxford University Press.

Lee, P. S., So, C. Y., & Leung, L. (2015). Social media and umbrella movement: Insurgent public sphere in formation. *Chinese Journal of Communication*, *8*(4), 356–375. https://doi.org/10.1080/17544750.2015.1088874

LeFebvre, R. K., & Armstrong, C. (2018). Grievance-based social movement mobilization in the# Ferguson twitter storm. *New Media & Society*, *20*(1), 8–28. https://doi.org/10.1177/1461444816644697

Lev-On, A. (2020). The igniter and the megaphone: Perceptions of facebook's role in activism. *Convergence: The International Journal of Research into New Media Technologies*, *26*(3), 577–592. https://doi.org/10.1177/1354856518792869

Lewin, T., & Jenzen, O. (2023). 21. LGBTQ+ visual activism. In D. Lilleker & A. Veneti. Eds. *Research handbook on visual politics* (pp. 268–283). Edward Elgar.

Lilleker, D., & Veneti, A. (Eds.). (2023). *Research handbook on visual politics*. Edward Elgar.

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. https://doi.org/10.1177/0022243719881113

Lu, Y., & Pan, J. (2021). Capturing clicks: How the Chinese government uses clickbait to compete for visibility. *Political Communication*, *38*(1/2), 23–54. https://doi.org/10.1080/10584609.2020.1765914

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. https://doi.org/10.1177/20563051221150406

Lynch, M. (2011). After Egypt: The limits and promise of online challenges to the authoritarian Arab state. *Perspectives on Politics*, *9*(2), 301–310. https://doi.org/10.1017/S1537592711000910

Mattoni, A., & Teune, S. (2014). Visions of protest. A media-historic perspective on images in social movements. *Sociology Compass*, *8*(6), 876–887. https://doi.org/10.1111/soc4.12173

McClain, C., Widjaya, R., Rivero, G., & Smith, A. (2022, April 28). *The behaviors and attitudes of U.S. adults on twitter*. Internet, Science & Tech. Retrieved June 1, 2022, from https://www.pewresearch.org/internet/2021/11/15/the-behaviors-and-attitudes-of-u-s-adults-on-twitter/

McDuffie, K., & Ames, M. (2021). Archiving affect and activism: Hashtag feminism and structures of feeling in women's March tweets. *First Monday*. https://doi.org/10.5210/fm.v26i2.10317

Messaris, P. (1997). *Visual persuasion: The role of images in advertising*. Sage.

Molina, M. D., Wang, J., Sundar, S. S., Le, T., & DiRusso, C. (2022). Reading, commenting and sharing of fake news: How online bandwagons and bots dictate user engagement. *Communication Research*, *50*(6), 667–694. https://doi.org/10.1177/00936502211073398

Muise, D., Lu, Y., Pan, J., & Reeves, B. (2022). Selectively localized: Temporal and visual structure of smartphone screen activity across media environments. *Mobile Media & Communication*, *10*(3), 487–509. https://doi.org/10.1177/20501579221080333

Neumayer, C., & Rossi, L. (2018). Images of protest in social media: Struggle over visibility and visual narratives. *New Media & Society*, *20*(11), 4293–4310. https://doi.org/10.1177/1461444818770602

Oeldorf-Hirsch, A. & Sundar, S. S. (2016). Social and technological motivations for online photo sharing. *Journal of Broadcasting & Electronic Media*, *60*(4), 624–642.

Ozduzen, O., & McGarry, A. (2020). Digital traces of "twitter revolutions": Resistance, polarization, and surveillance via contested images and texts of occupy gezi. *International Journal of Communication*, *14*, 2543–2563.

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. https://doi.org/10.1093/joc/jqy041

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. https://doi.org/10.1177/1940161220964769

Peng, Y., Lock, I., & Ali Salah, A. (2023a). Automated visual analysis for the study of social media effects: Opportunities, approaches, and challenges. *Communication Methods and Measures*, 1–23. https://doi.org/10.1080/19312458.2023.2277956

Peng, Y., Lu, Y., & Shen, C. (2023b). An agenda for studying credibility perceptions of visual misinformation. *Political Communication*, *40*(2), 225–237. https://doi.org/10.1080/10584609.2023.2175398

Rossi, L., Neumayer, C. & Vulpius, J. (2016). *Images of protest in contested social media: Production, propagation, and narratives*. AoIR Selected Papers of Internet Research.

Rössler, P., Bomhoff, J., Haschke, J. F., Kersten, J., & Müller, R. (2011). Selection and impact of press photography. An empirical study on the basis of photo news factors. *Communications*, *36*(4), 415–439. https://doi.org/10.1515/comm.2011.021

Ryan, T. J. (2012). What makes us click? Demonstrating incentives for angry discourse with digital-age field experiments. *The Journal of Politics*, *74*(4), 1138–1152. https://doi.org/10.1017/S0022381612000540

Shah, D. V., Hanna, A., Bucy, E. P., Lassen, D. S., Van Thomme, J., Bialik, K., Yang, J., & Pevehouse, J. C. (2016). Dual screening during presidential debates: Political nonverbals and the volume and valence of online expression. *American Behavioral Scientist*, *60*(14), 1816–1843. https://doi.org/10.1177/0002764216676245

Slovic, P., Västfjäll, D., Erlandsson, A., & Gregory, R. (2017). Iconic photographs and the ebb and flow of empathic response to humanitarian disasters. *Proceedings of the National Academy of Sciences*, *114*(4), 640–644. https://doi.org/10.1073/pnas.1613977114

Smith, L. G., McGarty, C., & Thomas, E. F. (2018). After Aylan Kurdi: How tweeting about death, threat, and harm predict increased expressions of solidarity with refugees over time. *Psychological Science*, *29*(4), 623–634. https://doi.org/10.1177/0956797617741107

Sobolev, A., Chen, M. K., Joo, J., & Steinert-Threlkeld, Z. C. (2020). News and geolocated social media accurately measure protest size variation. *American Political Science Review*, *114*(4), 1343–1351. https://doi.org/10.1017/S0003055420000295

Steinert-Threlkeld, Z. C. (2017). Spontaneous collective action: Peripheral mobilization during the Arab Spring. *American Political Science Review*, *111*(2), 379–403. https://doi.org/10.1017/S0003055416000769

Steinert-Threlkeld, Z. C., Chan, A., & Joo, J. (2022). How state and protester violence affect protest dynamics. *The Journal of Politics*, *84*(2), 798–813. https://doi.org/10.1086/715600

Sundar, S. S. (2008). *The MAIN model: A heuristic approach to understanding technology effects on credibility*. MacArthur Foundation Digital Media and Learning Initiative.

Sundar, S. S., & Limperos, A. M. (2013). Uses and grats 2.0: New gratifications for new media. *Journal of Broadcasting & Electronic Media*, *57*(4), 504–525. https://doi.org/10.1080/08838151.2013.845827

Sundar, S. S., Molina, M. D., & Cho, E. (2021). Seeing is believing: Is video modality more powerful in spreading fake news via online messaging apps? *Journal of Computer-Mediated Communication*, *26*(6), 301–319. https://doi.org/10.1093/jcmc/zmab010

Tait, G. B. (2023). Understanding the meanings of visuals: The motivations and values of black lives matter and social justice art activists. In D. Lilleker & A. Veneti (Eds.), *Research handbook on visual politics* (pp. 268–283). Edward Elgar.

Tarrow, S. (1993). Cycles of collective action: Between moments of madness and the repertoire of contention. *Social Science History*, *17*(2), 281–307. https://doi.org/10.2307/1171283

Tenenboim, O., & Cohen, A. A. (2015). What prompts users to click and comment: A longitudinal study of online news. *Journalism*, *16*(2), 198–217. https://doi.org/10.1177/1464884913513996

Theocharis, Y., Lowe, W., Van Deth, J. W., & García-Albacete, G. (2015). Using twitter to mobilize protest action: Online mobilization patterns and action repertoires in the occupy Wall Street, indignados, and aganaktismenoi movements. *Information, Communication & Society*, *18*(2), 202–220. https://doi.org/10.1080/1369118X.2014.948035

Tong, X., Li, Y., Li, J., Bei, R., Zhang, L. (2022). What are people talking about in# BackLivesMatter and# StopAsianHate? Exploring and categorizing twitter topics emerging in online social movements through the latent dirichlet allocation model Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society, July, 2022, 723–738, Oxford, United Kingdom.

Valensise, C. M., Serra, A., Galeazzi, A., Etta, G., Cinelli, M., & Quattrociocchi, W. (2021). Entropy and complexity unveil the landscape of memes evolution. *Scientific Reports*, *11*(1), 1–9. https://doi.org/10.1038/s41598-021-99468-6

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. https://doi.org/10.1111/jcom.12325

Walker, D., & Vul, E. (2014). Hierarchical encoding makes individuals in a group seem more attractive. *Psychological Science*, *25*(1), 230–235. https://doi.org/10.1177/0956797613497969

Wang, J., Sundar, S. S., & Vitak, J. (2022). Liking versus commenting on online news: Effects of expression affordances on political attitudes. *Journal of Computer-Mediated Communication*, *27* (6), zmac018. https://doi.org/10.1093/jcmc/zmac018

Wittenberg, C., Tappin, B. M., Berinsky, A. J., & Rand, D. G. (2021). The (minimal) persuasive advantage of political video over text. *Proceedings of the National Academy of Sciences*, *118*(47), e2114388118. https://doi.org/10.1073/pnas.2114388118

Yang, G. (2016). Narrative agency in hashtag activism: The case of #BlackLivesMatter. *Media and Communication*, *4*(4), 13–17. Article 13. https://doi.org/10.17645/mac.v4i4.692

Young, D. G., Jamieson, K. H., Poulsen, S., & Goldring, A. (2018). Fact-checking effectiveness as a function of format and tone: Evaluating FactCheck. org and FlackCheck. org. *Journalism & Mass Communication Quarterly*, *95*(1), 49–75. https://doi.org/10.1177/1077699017710453

Zell, A. L., & Moeller, L. (2018). Are you happy for me . . . on Facebook? The potential importance of "likes" and comments. *Computers in Human Behavior*, *78*, 26–33. https://doi.org/10.1016/j.chb.2017.08.050

Zhang, H., & Pan, J. (2019). CASM: A deep-learning approach for identifying collective action events with text and image data from social media. *Sociological Methodology*, *49*(1), 1–57. https://doi.org/10.1177/0081175019860244

Zhang, H., & Peng, Y. (2022). Image clustering: An unsupervised approach to categorize visual data in social science research. *Sociological Methods & Research*, 004912412210826. https://doi.org/10.1177/00491241221082603

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. https://doi.org/10.1109/TPAMI.2017.2723009

Zhou, A., & Yang, A. (2021). The longitudinal dimension of social-mediated movements: Hidden brokerage and the unsung tales of movement spilloverers. *Social Media + Society*, *7*(3), 20563051211047545. https://doi.org/10.1177/20563051211047545

Zhuravskaya, E., Petrova, M., & Enikolopov, R. (2020). Political effects of the internet and social media. *Annual Review of Economics*, *12*(1), 415–438. https://doi.org/10.1146/annurev-economics-081919-050239