

## Framing Social Movements on Social Media: Unpacking Diagnostic, Prognostic, and Motivational Strategies

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Social media enables activists to directly communicate with the public and provides a space for movement leaders, participants, bystanders, and opponents to collectively construct and contest narratives. Focusing on Twitter messages from social movements surrounding three issues in 2018-2019 (guns, immigration, and LGBTQ rights), we create a codebook, annotated dataset, and computational models to detect diagnostic (problem identification and attribution), prognostic (proposed solutions and tactics), and motivational (calls to action) framing strategies. We conduct an in-depth unsupervised linguistic analysis of each framing strategy, and uncover cross-movement similarities in associations between framing and linguistic features such as pronouns and deontic modal verbs. Finally, we compare framing strategies across issues and other social, cultural, and interactional contexts. For example, we show that diagnostic framing is more common in replies than original broadcast posts, and that social movement organizations focus much more on prognostic and motivational framing than journalists and ordinary citizens.

*Keywords:* framing, social movements, social media, Twitter

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Social movements use social media to draw attention to their cause, disseminate information, coordinate offline collective action, and build collective identity (Harlow, 2012; Jost et al., 2018). Given its prominent role, social media ought to be studied in the context of contemporary social movements, even if we cannot make outright causal claims about the effects of social media use on movement success (Kidd and McIntosh, 2016). At the core of social movements are networks of interactions between people with shared identities and goals (Diani, 1992); it is through these interactions that people collectively make sense of the world and the role of their movements in that world. We focus on this aspect of social movement communication, collective action framing, to characterize the discursive construction of social movements across three issue areas on Twitter from 2018-2019.<sup>1</sup>

*Framing* has diverse conceptualizations and operationalizations across disciplines, particularly cognitive linguistics, psychology, communication, and sociology (Cacciato et al., 2016). Primarily situated within sociology, social movement scholarship has largely adopted Goffman (1974)'s definition of frames as "schemata of interpretation" that help people "locate, perceive, identify, and label" new information about the world around them (Snow et al., 1986; van Dijk, 2023). Collective action frames are further strategic aspects of communication, "intended to mobilize potential adherents and constituents, to garner bystander support, and to demobilize antagonists" (Snow et al., 1988). We draw upon Benford and Snow's typology of *core framing tasks* (Snow et al., 1988; Benford and Snow, 2000). *Diagnostic* framing involves identifying problems, their causes, and who to blame or hold responsible. *Prognostic* framing involves articulating proposed solutions, plans of attack, and strategies or tactics for carrying out those plans. *Motivational* framing refers to motivating people to participate in the social movement through calls to action. This paper addresses the broad question: how do people accomplish diagnostic, prognostic, and motivational core framing tasks on Twitter?

We analyze a dataset of 1.85M tweets from movements in 2018-2019 surrounding three issue areas: *guns*, *immigration*, and *LGBTQ rights*, primarily within the U.S. context. We first develop a codebook, which we use to manually annotate a sample of 6,000 tweets for relevance, stance, and diagnostic, prognostic, and motivational framing strategies. We then

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<sup>1</sup>Twitter rebranded as X in July 2023. However, we use the terms "Twitter" and "tweets" throughout this paper as they accurately describe the platform during the time period that we study.

use supervised machine learning techniques to infer labels for the rest of the tweets in our dataset. By enabling us to analyze framing at scale, our automated data labeling approach facilitates a more comprehensive description of social movement discourse on Twitter than small-N samples. We then conduct a fine-grained linguistic analysis of each core framing task to better understand how social movements create meaning from raw textual material (Vicari, 2010). We show the prevalence of moral language across issue areas and core framing tasks, and highlight how core framing tasks differ in their personal pronoun usage, suggestive of boundary framing processes (Snow et al., 1986).

The resulting large-scale labeled dataset allows for the investigation of fine-grained temporal patterns and comparisons of framing across many cross-sections of data. In particular, we explore how attention to each core framing task varies across a set of movement-level sociocultural dimensions, including issue area, ideology, and offline protest activity levels. We also compare framing across several message-level interactional factors, namely the author’s role (as a journalist, social movement organization, or member of the public) and tweet type (traditional “broadcast” tweets versus quote tweets and replies). Our results suggest a degree of stability in framing practices, especially over time and within the same ideology across issues. At the same time, we uncover significant frame variation across several factors. For example, social movement organizations employ far more *prognostic* and *motivational* framing than their journalist and general public counterparts. We also show substantial variation across tweet types, with replies and quote tweets being much more likely to contain *diagnostic* framing than broadcasts. Taken altogether, our work emphasizes both the importance of message context and the value of a consistent methodology when studying social movement communication.<sup>2</sup>

## Background

We first introduce the framing perspective in social movement studies and discuss the interplay between social media affordances and social movement communication. We specifically highlight prior work that analyzes movements’ engagement with diagnostic, prognostic, and motivational core framing tasks. We then motivate our selection and investigation of

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<sup>2</sup>Our dataset, annotation codebook, code, and models are all available at: <https://github.com/juliamendelsohn/social-movement-framing/>

frame variation and alignment across multiple sociocultural dimensions, including stance, offline events, author roles, and audiences. Next, we provide a brief overview of the three issue areas that we study: *gun policy/violence*, *immigration*, and *LGBTQ rights*. We conclude this section with a review of computational approaches to frame analysis.

**Framing and Social Movements.** Social movements are sustained efforts to enact or hinder social and political changes (Jasper, 2014), and are characterized by networks of interactions between individuals and groups united by shared collective identities (Diani, 1992; Della Porta and Diani, 2006). Since the 1980s, scholars have embraced framing as a cultural perspective to complement predominant theories of resource mobilization and political opportunity structure (Snow et al., 1986). Framing refers to the dynamic, interactive process of constructing and negotiating shared meaning of a movement (Snow et al., 1986), “involving various actors within a discursive context consisting of movement activists, actual and potential adherents, countermovement proponents, social control agents, government and social policy agents, the media, and often a watchful public” (Snow and Vliegenthart, 2023). Effective framing is associated with protest participation and movement success (Cress and Snow, 2000; Della Porta and Diani, 2006; Somma and Medel, 2019).

Social movement research has traditionally taken interpretive approaches to analyze framing practices on a macro-scale, at the group or movement-level (Gerhards and Rucht, 1992). However, critics both within and outside the field have called for more empirical studies (Benford, 1997; Snow et al., 2014), and advocate for a greater focus on micro-level frame analysis within interactions on both theoretical and methodological grounds (Johnston, 1995; Johnston and Alimi, 2013; Hedley and Clark, 2007; Vicari, 2010, 2023; Gordon and Tannen, 2023; van Dijk, 2023). Methodologically, micro-frame analysis of individual texts “enables the researcher to speak about frames with a great deal more empirical grounding” (Johnston, 1995). Theoretically, movement-level frames emerge through the aggregation, contestation, layering, and transformation of framing within individual messages or interactions (Hedley and Clark, 2007). Analysis at the micro-level sheds light on the dynamic processes associated with framing, and helps “illuminate moment-by-moment constructions of meanings, identities, and relationships” (Gordon and Tannen, 2023).

**Social Movements and Social Media.** Social media has upended many tradi-

tional assumptions about collective action (Kavada, 2016). In contrast to the high organizational structure, emphasis on collective identity, and rigid collective action frames in offline collective action, Bennett and Segerberg (2011, 2012) argue that social media engenders a new logic of “connective action” based on personalization of content and frames to mobilize different audiences. It facilitates a hybrid environment in which activists, bystanders, news media, and politicians all participate and interact to negotiate meanings of collective actions (Pavan, 2014; Barnard, 2018). Meraz and Papacharissi (2013) articulate “networked framing” in such environments as a process by which frames are “persistently revised, rearticulated, and redispersed by both crowd and elite” and ought to be interpreted in the context of the ambient conversations taking place concurrently on the platform.

Marked by this hybridity and decentralized communication, social movement scholarship has interrogated connections between social media activism and shifts in the distribution of power (Dimond et al., 2013). Movements may be able to gain public attention (a key resource for mobilization) and share their own narratives without relying on traditional gatekeepers such as mass media (Tufekci, 2013; Mundt et al., 2018; Molder et al., 2022). There may also be shifts in power within social movements themselves. For example, scholars debate the role of centralized formal social movement organizations (SMOs) in online protest (Earl, 2015; Spiro and Monroy-Hernández, 2016; Bozarth and Budak, 2021). Some argue that leadership still exists in online social movements, but takes a different shape, where opinion leaders may include not only SMOs, but also ordinary citizens, celebrities, and community administrators (Poell et al., 2016; Gerbaudo, 2017; Pond and Lewis, 2019; Liang and Lee, 2021; Uysal et al., 2022).

Social movements have leveraged platform affordances in many other ways, such as for building collective identity (Harlow, 2012; Milan, 2015; Flores-Saviaga et al., 2018). Platforms such as Twitter facilitate forming connections between people with shared interests and values who may have no geographic proximity or other offline ties with each other (Tremayne, 2014; van Haperen et al., 2023). Through both algorithmic curation and crowd collaboration, social media affordances enable movement actors to consume, share, recommend, and filter information (Starbird and Palen, 2012; Meraz and Papacharissi, 2013; Tillery, 2019; Etter and Albu, 2021), including coordination of offline protest (Harlow, 2012; Earl et al., 2013; Jost et al., 2018; Tsatsou, 2018). Prior work has also analyzed framing

through the use of technological features such as hashtags (Meraz and Papacharissi, 2013; Ince et al., 2017) and reposts (Nip and Fu, 2016).

A much smaller body of work has coded and described diagnostic, prognostic, and motivational framing strategies in social media posts to analyze a variety of movements, primarily focusing on prominent activists and organizations. Using Benford and Snow (2000)'s definition of these core framing tasks, Vu et al. (2021) analyze framing by climate change organizations on Facebook and Molder et al. (2022) qualitatively analyze youth climate activist Greta Thunberg's Instagram posts. Hon (2016) conducts a qualitative analysis of the Facebook page from the Million Hoodies racial justice movement to identify how the movement engages with each core framing task. Phadke et al. (2018) and Phadke and Mitra (2020) compare how hate groups frame their hate-based movements on Facebook and Twitter by developing a fine-grained typology of domain-specific frame components within diagnostic, prognostic, and motivational framing. In the context of protest against the Singaporean government's immigration policy changes, Goh and Pang (2016) compare organizers' and protestors' framing strategies in blogs and Facebook posts. The authors develop sub-categories within each framing task through exploratory analysis guided by Benford and Snow's definitions, such as coding sub-categories of the diagnostic frame for problem, victim, and causal agent identification. The current study differs substantially from these works in domain, methodology, scale, and broad research questions. Nevertheless, they inspire us to pursue a similar strategy in creating our codebook, particularly in identifying several sub-categories for diagnostic and prognostic framing.

**Frame Variation.** Despite many studies on social movement framing, little attention has been dedicated to empirical analyses of frame variation across sociocultural contexts (Snow et al., 2014). Given the importance of moving beyond single case studies and pursuing comparative work in social movement studies (Tarrow, 1996), we heed Snow et al. (2014)'s call for comparisons of framing across movements, actors, and time, and here briefly motivate the sociocultural dimensions that we study.

Movements co-exist and engage with other movements, and the same actors may participate in multiple movements across different issue areas (Carroll and Ratner, 1996). Cultural practices, including framing, have also been shown to diffuse both within and

across movements (Soule and Roggeband, 2018). Movements also exist in direct competition with opposing countermovements. As one of the primary goals of collective action framing is to “demobilize antagonists” (Snow et al., 1988), frames develop over the course of sustained interaction with countermovements (Ayoub and Chetaille, 2020). Movement and countermovement frames may be closely-aligned, especially when drawing from the same cultural themes (Ayoub and Chetaille, 2020; Sun et al., 2023). At the same time, movements may develop frames to challenge or contest the opposition’s (McCaffrey and Keys\*, 2000; Stewart et al., 2017). Framing may also vary due to differences in movement and countermovement opportunities and constraints; for example, *gun rights* organizations’ financial advantages over *gun control* organizations allow them to rely less on “attention-grabbing moments” (Laschever and Meyer, 2021). Framing processes are closely intertwined with collective action activity. Not only are frames deployed in order to mobilize collective action participation (Benford and Snow, 2000), but they also evolve during cycles of protest (Snow and Benford, 1992). Framing practices further shift in response to protest waves or even individual collective action events (Ellingson, 1995; Swart, 1995; Valocchi, 2006).

Social movement discourses on online platforms, particularly hybrid media environments such as Twitter, are characterized by the presence of and interactions between many groups of stakeholders, including social movement organizations (SMOs), journalists, and ordinary citizens (Meraz and Papacharissi, 2013; Jackson and Foucault Welles, 2016; Caren et al., 2020; Isa and Himelboim, 2018; Hunt and Gruszczynski, 2023). These stakeholder groups each have different goals and complex relationships with each other, through which framing takes center stage. On one hand, SMOs seek to gain media attention and influence news coverage (Andrews and Caren, 2010; Gibson, 2023). On the other hand, news media frequently offers delegitimizing frames of protestors to uphold the status quo through the “protest paradigm” (McLeod and Detenber, 1999). However, more recent work has found news media to also offer more sympathetic and legitimizing coverage that considers protestors’ grievances and demands (Mourão et al., 2021; Gruber, 2023). In digitally-mediated social movements, journalists have even found themselves alongside SMOs as core movement actors who mediate the flow of relevant information (Isa and Himelboim, 2018).

The role of SMOs in online movements remains unclear. Given the centrality of SMOs in pre-digital movements, a major focus of earlier framing research has been in frame

alignment between SMOs and the populations they seek to mobilize (Snow et al., 1986). As social media offers more opportunities for individual citizens to become opinion leaders (Meraz and Papacharissi, 2013; Jackson and Foucault Welles, 2016), the utility and necessity of SMOs has come into question (Earl and Schussman, 2002; Earl, 2015). At the same time, SMOs remain a central source of information, offer credibility and legitimacy, have greater capacity to organize offline collective action, and may even be more successful in collective identity formation and recruitment online than their non-organizational counterparts (Earl, 2015; Bozarth and Budak, 2017; Hunt and Gruszczynski, 2023).

Social movements' understanding of their audiences can also shape their framing strategies (Snow et al., 1986; Blee and McDowell, 2012), and movements often customize their framing to appeal to different subsections of their audience (Andersen and Sandberg, 2020; Bergstrand and Whitham, 2022). This is exemplified in online movements, where personalized content sharing allows for greater flexibility in adapting frames to mobilize diverse audiences, as opposed to relying on singular rigid collective action frames (Bennett and Segerberg, 2011, 2012). On Twitter, posts are public by default and visible to one's full list of followers and beyond. However, people have diverse strategies to navigate this "context collapse" to reach intended sub-audiences (Marwick and boyd, 2011), such as through addressivity markers (Meraz and Papacharissi, 2013). Twitter's interactional features offer another mechanism for targeting intended audiences; different types of tweets (original "broadcast" tweets, quote tweets, and replies) have different intended audiences and communicative goals (Garimella et al., 2016).

**Issue Areas.** We offer a brief background of major events in the United States from the time period we studied (2018-2019) that pertain to each issue area that we consider.

**Guns.** On February 14, 2018, a gunman killed 17 people and wounded 17 others at Marjory Stoneman Douglas High School in Parkland, Florida (Aslett et al., 2022). In the wake of the tragic event, Parkland student survivors organized the March for Our Lives campaign, which rapidly gained national and international attention and reignited a long-standing political conflict over gun policy (Laschever and Meyer, 2021). March for Our Lives campaigned for and lobbied political leaders for increased gun control measures. Most notably, the student activists coordinated school-based, local, and national protests on a

massive scale; the eponymous march in Washington D.C. and 764 other satellite locations drew 1.4 to 2.2 million participants, and the National Student Walkout on March 14, 2018 drew 1.1 to 1.7 million participants at 4,495 locations (Pressman et al., 2022). The gun rights countermovement also mobilized during this time (Laschever and Meyer, 2021).

Prior research has studied framing on Twitter and in news coverage following mass shootings, with a particular focus on partisan polarization (Demszky et al., 2019; Lin and Chung, 2020; Holody and Shaughnessy, 2022; Zhang et al., 2022). Several articles have also compared framing strategies between gun control and gun rights SMOs (Steidley and Colen, 2017; Merry, 2018). While gun control SMOs focus on child victims and mass shootings, gun rights SMOs focus on self-defense (Merry, 2018). Following the Parkland shooting, gun control SMOs further identified easy gun access as a problem and emphasized mobilization, while gun rights SMOs focused more on law enforcement's failures (Aslett et al., 2022). Focusing on student activists' diagnostic, prognostic, and motivational framing on Twitter, Zoller and Casteel (2022) finds that students identify lax gun policy as a problem, and frequently blame the NRA and their political influence. Prognostic framing includes promoting gun control legislation as a solution and boycotting/refusing NRA money as a tactic (Zoller and Casteel, 2022). Surprisingly, gun control SMOs, including March for Our Lives, tend not to focus on race, even though gun violence primarily affects communities of color (Merry, 2018; Tergesen, 2021)

**Immigration.** In May 2018, the U.S. Department of Justice under the Trump Administration implemented a “zero tolerance” policy at the U.S.-Mexico border, which required that all adult migrants who cross the border without permission be prosecuted while any children they crossed with were sent to separate detention facilities (Alamillo et al., 2019). This represented a stark contrast to prior policy, in which families were kept together, either while awaiting their immigration cases or in deportation. In early June 2018, mainstream media outlets covered several individual cases of harm that this family separation policy caused.<sup>3</sup> In response, on June 15, the Department of Homeland Security publicly acknowledged that nearly 2,000 children had been separated from their families, and there was no clear plan for reunification. Media coverage, as well as public outrage,

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<sup>3</sup><https://www.splcenter.org/news/2022/03/23/family-separation-timeline>

intensified when journalists and human rights advocates toured one of the children detention centers and reported on the poor conditions on June 17. After several days of escalating pressure, Trump signed an executive order on June 20 to end the family separation policy. In analyzing news coverage of the family separation crisis, Alamillo et al. (2019) finds that most mainstream media outlets emphasized humanitarian concerns, particularly the harms that separations have on young children. Fox News, however, often talked about the risk of human trafficking at the border (Alamillo et al., 2019).

While media framing of immigration, immigrants, refugees, and asylum-seekers has been widely studied (Eberl et al., 2018; Seo and Kavakli, 2022), immigrant rights movements have only relatively recently been integrated into social movement scholarship (Mora et al., 2018). Pro-immigration SMOs tailor their framing to different audiences in order to address “four categories of aims: educating and persuading the general public, engaging non-supporters through dialogue, supporting and organizing migrants as activists, and building cooperative relationships with the authorities” (DeTurk, 2023). There has been related work on refugee discourse and activism through Twitter affordances (Siapera et al., 2018; Estrada et al., 2021). For example, Estrada et al. (2021) find that pro-refugee activists use the #IAmARefugee hashtag on Twitter to express solidarity and engage in boundary work in opposition to Trump’s “Muslim Ban”, discursively constructing a moral “us” and an immoral “them”. Finally, a small set of articles have analyzed diagnostic, prognostic, and motivational framing in the context of immigration, particularly among anti-immigration activists and the far-right (Dove, 2010; Gagnon, 2020; Wahlström et al., 2021).

**LGBTQ rights.** The contemporary LGBTQ rights movement has a long history in the U.S., with collective action frames emerging from the homophile movement in the 1950s and the civil rights protest wave in the 1960s (Valocchi, 2006). Since the 1969 Stonewall uprising, Pride protests have been held annually in June and now occur in many cities in the U.S. and worldwide.<sup>4</sup> We analyze Twitter data about LGBTQ rights from 2018-2019. This was several years after the 2015 Obergefell v. Hodges Supreme Court case that federally legalized same-sex marriage (Espinoza-Kulick, 2020), but before the massive wave of anti-trans legislation in the 2020s.<sup>5</sup> The Crowd Counting Consortium counted 3.7 million

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<sup>4</sup><https://www.loc.gov/lgbt-pride-month/about/>

<sup>5</sup><https://translegislation.com/learn>

protest participants in June 2018, primarily from Pride events (Pressman et al., 2022), with the majority of Pride participants attending demonstrations on June 24, 2018, when many major US cities including New York, San Francisco, Chicago, and Seattle, hosted parades.

LGBTQ activists and the Religious Right have been embroiled in a decades-long movement/countermovement dynamic that mutually participate in each others' framing processes (Liebler et al., 2009; Stone, 2016). As such, much prior work on framing with respect to LGBTQ rights has focused on comparisons between proponents and opponents of same-sex marriage in news coverage; while pro-LGBTQ activists emphasize civil rights and equality considerations, anti-LGBTQ activists frame same-sex marriage as a threat to Christian values and “traditional” heterosexual marriage (Hull, 2001; Warren and Bloch, 2014). Several papers have analyzed pro-LGBTQ and anti-LGBTQ dynamics on Twitter from the collective action perspective (Copeland et al., 2016; Oktavianus et al., 2023). For example, Oktavianus et al. (2023) shows that in the context of the anti-LGBTQ #UninstallGojek in Indonesia, anti-LGBTQ protestors primarily engaged with prognostic and motivational framing, while the pro-LGBTQ counterprotestors emphasized diagnostic considerations.

**Computational Framing Analysis.** There has been growing interest in automated frame detection to facilitate large-scale textual analysis. Computational approaches broadly fall into two camps: unsupervised and supervised methods, which parallel inductive and deductive coding in social sciences, respectively. Topic modeling is a popular unsupervised method, and has been used to analyze framing in news articles (Walter and Ophir, 2019), social media posts (Tschartky and Makhortykh, 2023), and online social movements such as Black Lives Matter, Me Too, climate advocacy, and the digitally-native Sleeping Giants movement (Li et al., 2021b,a; Chen et al., 2022; Klein et al., 2022). Most closely aligned with our work, Aslett et al. (2022) use topic modeling to study frame contests between gun control and gun rights groups following the 2018 shooting at Marjory Stoneman Douglas High School in Parkland, Florida. They find that gun rights organizations emphasized the inefficacy of gun restrictions and highlighted law enforcement failure as the primary problem, while gun control groups identified easy access to guns as the main problem and emphasized mobilization. However, scholars argue that unsupervised approaches like topic modeling do not capture theoretically-grounded frames, in contrast to supervised classification with existing taxonomies (Nicholls and Culpepper, 2021; Eisele et al., 2023).

Supervised frame detection involves first manually coding texts based on a pre-existing frame taxonomy, and then using this labeled data to train machine learning classification models. Prior work has implemented a wide variety of supervised classification models to detect frames, including support vector machines, random forest classifiers, neural networks, and fine-tuning pretrained language models such as RoBERTa (Khanehzar et al., 2019, 2021; Ali and Hassan, 2022; Eisele et al., 2023). A recent but quickly-growing body of literature is also exploring the potential of prompting large language models (e.g., ChatGPT) for both supervised and unsupervised frame analysis (Guo et al., 2022; Mou et al., 2022; Roy et al., 2022; Ziems et al., 2023).

Especially within the field of NLP, much computational framing research uses the Policy Frames Codebook of issue-generic frames in U.S. news media (Boydston et al., 2013, 2014) and the associated Media Frames Corpus for training models (Card et al., 2015). In addition to news media, the Policy Frames Codebook has been used to analyze social media data, including politicians' tweets (Johnson et al., 2017), public tweets about immigration (Mendelsohn et al., 2021), and online discussion posts (Hartmann et al., 2019). The Policy Frames Codebook has also been deployed in analyzing news and social media data in non-English languages outside of the U.S. (Piskorski et al., 2023; Park et al., 2022). Other work has similarly focused on supervised frame detection of Semetko and Valkenburg (2000)'s typology of issue-generic news frames (Burscher et al., 2014; Kroon et al., 2022; Alonso del Barrio and Gatica-Perez, 2023). Although to a lesser extent, there has also been computational work considering other perspectives on framing, including entity-centric framing (Ziems and Yang, 2021; Frermann et al., 2023) and morality framing (Roy et al., 2022).

Several papers have developed corpora and computational models to identify issue-specific media frames for gun violence (Liu et al., 2019a; Akyürek et al., 2020; Tourni et al., 2021) and immigration (Mendelsohn et al., 2021). We investigate these same issue areas but draw from a different theoretical framework focused on diagnostic, prognostic, and motivational core framing tasks for collective action mobilization (Benford and Snow, 2000). Little prior work has focused on automatically classifying these core framing tasks, with several notable exceptions. Hsu et al. (2016) use supervised machine learning to classify diagnostic, prognostic, and motivational framing in messages from the Taiwanese anti-curriculum student movement. Alashri et al. (2016) and Fernandez-Zubieta et al. (2022) build supervised

models to detect these core framing tasks in news articles and social media posts about climate change and climate action. Social movement scholars recognize the need for empirical, large-N, and comparative framing research in addition to in-depth interpretive case studies (Snow et al., 2014), but such endeavors have been limited by the relative lack of sociologically-grounded computational approaches. Our work addresses this methodological gap and showcases the utility of computational methods for such empirical analyses.

## Data

We now turn to our data collection, codebook creation, and annotation procedures. We first manually annotate framing strategies in a random sample of data in order to train models to automatically infer labels for the entire dataset of nearly two million tweets.

**Data Collection.** We study the framing of online social movements with data from Bozarth and Budak (2022), which contains tweets from the Twitter Decahose 10% sample from 2018-2019. Using collective action event, participation, and issue area data from the Crowd Counting Consortium (CCC),<sup>6</sup> Bozarth and Budak (2022) select five issue areas that have the most variance in the number and size of their associated collective action events: *government, healthcare, LGBTQ rights, guns, and immigration*. They collect data from two months for each issue: one month characterized by high protest activity and one month with average levels of protest activity. We then select a subset of this data that covers three issue areas: *guns, immigration, and LGBTQ rights* for two reasons. First, these three issue areas have one overlapping month of data (June 2018), which facilitates direct comparisons. Second, we manually inspect the collective action event claims (another field in the CCC data) and qualitatively observe that events for these three issue areas had more cohesive and unified goals, and are thus more closely aligned with our conceptualization of social movements.

For each issue area, Bozarth and Budak (2022) develop lexicons for keyword-based tweet collection by combining and validating a set of machine learning and embedding-based keyword expansion techniques, starting with a seed set of frequent hashtags posted during collective action events. Note that Bozarth and Budak (2022) do not distinguish between

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<sup>6</sup><https://github.com/nonviolent-action-lab/crowd-counting-consortium>

progressive and conservative movement activities, and thus opposing movements surrounding the same issues are represented. For example, both *guncontrolnow* and *guncontrolnever* are keywords for the *guns* issue area. The resulting dataset contains 1.85M tweets in total, with 822K tweets about *guns*, 763K tweets about *immigration*, and 268K tweets about *LGBTQ rights*. The dataset includes replies and quote tweets, but excludes retweets with no additional commentary. The counts by month are shown in Table 1. Major actions during high activity months include Pride parades for *LGBTQ rights*, protests against family separation at the US-Mexico border for *immigration*, and youth-led demonstrations following the school shooting in Parkland, Florida for *guns*.

We opt to use this dataset as it provides several distinctive advantages for social movement framing analysis. Twitter has long been recognized as a primary site for social movement activism (Meraz and Papacharissi, 2013); the high volume of relevant messages on Twitter facilitates both rich cross-sectional and fine-grained temporal analyses of framing strategies. The metadata linked to tweets, such as the exact time of posting and author information, further enable such analyses. In contrast with many other datasets that focus on a single social movement, Bozarth and Budak (2022)'s dataset is particularly valuable because it covers multiple issues with active associated movements in the same time period. Moreover, each issue area encompasses both progressive and conservative movements, providing the opportunity for comparative content analysis across both issue and ideological stances. With data from months with both high and average levels of offline collective action activity, Bozarth and Budak (2022)'s dataset can help us understand the relationship between online discourse and offline events. Finally, this dataset was collected with a validated keyword expansion method that retrieves a much broader set of tweets than those collected via single keywords or hashtags.

At the same time, this dataset presents several limitations that can be addressed in future work. While the dataset includes months characterized by different levels of activity for each issue area, it still encompasses a relatively small stretch of time from 2018-2019. It is also limited to one social media platform that may not necessarily be representative of all social movement communication. The inclusion of multiple issue areas is a key advantage of this dataset, but there are many issue areas that are not considered, particularly outside of the US context. The dataset and our methodology exclusively focus on textual

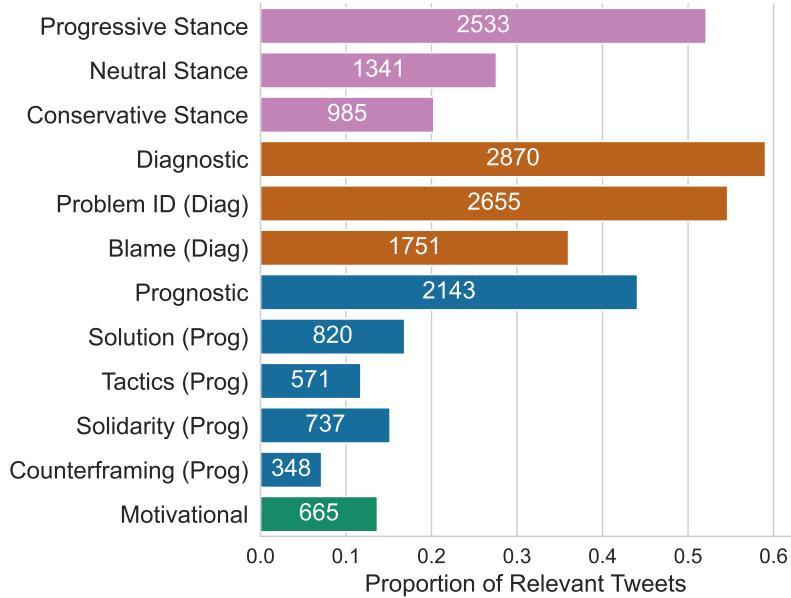
communication, and do not include modalities such as audio, video, or images. While out of scope for the present work, future research ought to investigate if the findings from our data generalize to other issues, platforms, time periods, languages, modalities, and cultural contexts.

**Table 1: Monthly tweet counts by issue and protest activity level**

Issue	Protest Activity	Month	Tweet Count
guns	high	March 2018	633,027
guns	average	June 2018	189,134
immigration	high	June 2018	513,284
immigration	average	July 2018	249,776
LGBTQ rights	high	June 2018	172,006
LGBTQ rights	average	April 2019	95,695

**Table 2: Annotation typology and codebook descriptions for stance, core framing tasks, and frame elements**

Category	Sub-Category	Brief Codebook Description
Stance	Stance	Based on the text, would you guess that this message was written by someone with a progressive, conservative, or neutral/unclear attitude towards the specified issue?
Diagnostic	Identification	Does this message identify a social or political problem? <i>Ex: homophobia, school shootings, family separation at the border</i>
	Blame	Does this message assign blame for a societal problem? <i>Ex: to the government, corporations, socioeconomic systems</i>
Prognostic	Solutions	Does this message propose solutions for a societal problem? <i>Ex: changes in policies, political leaders, or societal norms</i>
	Tactics	Does this message discuss strategies or tactics for achieving a movement's goals? <i>Ex: protests, boycotts, petitions, contacting politicians</i>
	Solidarity	Does this message express support or solidarity for a movement? <i>Ex: celebrating a movement, honoring activists, raising visibility</i>
Motivational	Counterframing	Does this message explicitly challenge arguments made by the opposing side?
	Motivational	Does this message try to convince readers to join, participate in, or support a social movement through calls to action?



**Figure 1. Label prevalence in the annotated dataset.**

*Note.* As a proportion of relevant tweets. Raw counts are shown inside the bars.

### Annotation

We developed and iteratively refined a codebook based on theoretical definitions (Benford and Snow, 2000; Della Porta and Diani, 2006) and existing codebooks for characterizing diagnostic, prognostic, and motivational framing strategies (Goh and Pang, 2016; Phadke et al., 2018; Phadke and Mitra, 2020).

**Framing Typology.** Because Boolean keyword search by itself is a coarse proxy for relevance, we follow Bozarth and Budak (2022)'s suggestion to first categorize tweets as *relevant or irrelevant* to an issue area. We further code relevant tweets for *stance* and *diagnostic, prognostic, and motivational* framing strategies (Table 2). Stance can take one of three mutually-exclusive values: progressive (pro-gun control, pro-immigration, pro-LGBTQ), conservative (pro-gun rights, anti-immigration, anti-LGBTQ), or neutral/unclear from the text. Guided by Benford and Snow (2000) and Goh and Pang (2016), we operationalize and code for diagnostic framing based on the presence of any of two sub-categories: *problem identification* and *blame attribution*. Similarly, we code for prognostic framing based

on the presence of any of four sub-categories based in Benford and Snow (2000)'s definition: proposing *solutions*, discussing movement *tactics*, expressing *solidarity*, and engaging in *counterframing*. Throughout this paper, we refer to the broader framing categories as **core framing tasks**, and the narrower sub-categories as **frame elements**. Note that motivational framing was directly coded, and is thus considered both a core framing task and a frame element.

**Table 3: Label prevalence in the annotated dataset by issue area.**

	Guns	Immigration	LGBTQ
Progressive Stance	566	627	1340
Neutral Stance	357	477	507
Conservative Stance	362	519	104
Diagnostic	761	1172	937
Problem ID (Diag)	661	1079	915
Blame (Diag)	517	837	397
Prognostic	644	689	810
Solution (Prog)	258	435	127
Tactics (Prog)	256	141	174
Solidarity (Prog)	112	83	542
Counterframing (Prog)	154	123	71
Motivational	220	208	237

Starting with a preliminary codebook, the first author and two undergraduate research assistants completed a pilot annotation task of 150 tweets. From the resulting discussions, we adapted the codebook for Twitter data, expanded the neutral stance code to include tweets with unclear stance, and identified the need for a separate *solidarity* frame element (Hon, 2016). The first author and one undergraduate research assistant proceeded to conduct several iterations of annotator training. Each iteration consisted of 150 tweets, evenly split across issues and protest activity periods. After independent labeling, annotators met to resolve all disagreements and agree on any minor clarifications and modifications to the codebook. Inter-annotator agreement (Krippendorff's  $\alpha$ ) was calculated after each round and sufficient agreement was reached after five rounds, with  $\alpha \geq 0.75$  for all categories except for *counterframing* for which  $\alpha = 0.66$ . Following the fifth round, annotators proceeded independently until a total of 6,000 tweets were labeled (equally distributed across issues and protest activity level periods). 4,859 (81%) of these tweets were coded as *relevant* and further coded for stance and framing.

The overall presence of each stance and framing category in our manually-labeled dataset is shown in Figure 1, and separated by issue area in Table 3. *Progressive* stance and *diagnostic* framing are the most frequent categories overall, while *counterframing*, *tactics*, and *motivational* framing are the least frequent categories. However, this varies across issues. For example, *solidarity* is much more frequent for LGBTQ-related tweets than for other issues, while *solution* is less frequent. Tweets may cue anywhere from zero core framing tasks to all three (Table 4). The plurality of relevant tweets in all issue areas engages in one core framing task. About 19% of relevant tweets are not labeled with any collective action framing strategies. While these tweets are relevant to issue areas, they tend to not be as relevant to particular social movements. Many tweets with no frame labels are jokes, posts about author's typical everyday experiences, or short direct responses to unobserved tweets or external links with little additional information.

**Table 4: Number of core framing tasks in tweets.**

Frame Count	Guns	Immigration	LGBTQ	Total
0	223	244	444	911
1	618	810	1091	2519
2	325	448	355	1128
3	119	121	61	301
Average	1.26	1.27	1.02	1.17

*Note.* Number of tweets containing zero, one, two, or three core framing tasks, and the average number of core framing tasks in each tweet separated by issue area.

### Classifying Framing Strategies

We operationalize our taxonomy as a set of four classification problems. First is binary **relevance** classification. Second is a 3-class **stance** classification, where the *progressive*, *conservative*, and *neutral/unclear* outputs are mutually exclusive. Third is **core framing task** classification. Because a tweet may be labeled with none, some, or all three of the *diagnostic*, *prognostic*, and *motivational* strategies, we treat this as a binary, multi-label problem. Fourth is **frame element** classification, which includes the seven frame elements that were directly coded for (*problem identification*, *blame*, *solution*, *tactics*, *solidarity*, *counterframing*, and *motivational*). This is similarly a binary multi-label classification problem where anywhere from 0-7 frame elements may be present in a tweet.

**Model Setup.** For each of these four classification problems, our goal is to train computational models to predict the appropriate labels. We use a common approach in NLP, where we build our classifiers on top of RoBERTa (Liu et al., 2019b), a highly-parameterized pretrained language model, which has been trained on vast amounts of unlabeled data. Following standard practice, we first finetune the parameters of the RoBERTa-base model on the full corpus of 1.85M tweets in order to adapt the language model to better recognize linguistic patterns in tweets related to social movements.<sup>7</sup> We then separately train the finetuned RoBERTa model for each of the four classification tasks. We split our labeled sample into training and testing splits, containing 80% and 20% of the data, respectively. Within the training set, we use 5-fold cross-validation to refine and compare models. We train separate models for each issue, as well as a combined model that includes data from all issues in training and evaluation.<sup>8</sup> Given that we expect framing strategies to somewhat generalize across issues, we first consider whether to treat issues together or separately. As part of our preliminary investigation, we first compare training separate models for each issue, as opposed to pooling data from all issues, and using that combined data for training models that do not explicitly distinguish between issues.

**Model Evaluation.** Based on preliminary experiments, with results in Table 5, combined-issue models trained on pooled data across issues outperform issue-specific models. We thus decide to proceed with the combined-issue models for further evaluation and analysis. The higher test set performance is likely due to our cross-validation setup. Each development model was only trained on 4/5 folds of the training set (64% of the total dataset). Models evaluated on the test set were trained on the full training set (80% of the total dataset).<sup>9</sup>

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<sup>7</sup>All RoBERTa-based models were trained using the `simpletransformers` package. We finetuned RoBERTa for five epochs with a batch size of 128, with all other hyperparameters set to the package defaults. Using two NVIDIA V100 GPUs, finetuning took slightly under three hours.

<sup>8</sup>We trained each classifier on one GPU for 20 epochs and a batch size of 32. Each model was trained in under 30 minutes.

<sup>9</sup>Note that we do not deduplicate our data because our primary goal is to make accurate predictions on the full dataset. As such, these numbers may give an artificially high sense of model performance, because there will be either identical or near-identical tweets that exist in both training and testing data. We partially mitigate this problem by excluding retweets (but not quote tweets) from our dataset. Although further deduplication could be used to get more precise estimates of performance on truly unseen data, this would be both difficult to accomplish effectively (because of near-duplicate tweets) and would give less meaningful estimates for our goals.

**Table 5: Average F1 scores for combined-issue and issue-specific models.**

Split	Training Data	Evaluation Issue		
		Guns	Immigration	LGBTQ
Development	All Issues	<b>0.710 (0.121)</b>	<b>0.697 (0.177)</b>	<b>0.673 (0.234)</b>
	Single Issue	0.680 (0.145)	0.651 (0.223)	0.634 (0.267)
Test	All Issues	<b>0.734 (0.121)</b>	<b>0.709 (0.153)</b>	<b>0.694 (0.204)</b>
	Single Issue	0.706 (0.117)	0.679 (0.218)	0.643 (0.248)

*Note.* The scores shown are averages of F1 scores per label. Standard deviations are in parentheses. Development scores are averaged over five cross-validation folds.

**Table 6: Stance classification F1-scores by issue, evaluated on the test.**

Issue	Liberal	Neutral	Conservative
Guns	0.824	0.559	0.652
Immigration	0.763	0.582	0.798
LGBTQ	0.879	0.656	0.410

We observe high performance of the combined-issue relevance classifier, with a test F1 score of 0.968 (precision = 0.959, recall = 0.976). Table 6 (and Appendix Table A1) show per-issue stance classification F1-scores. Likely due to the skew towards *liberal* tweets in the training data, performance is overall highest for *liberal* tweets, though the stance model has high performance for identifying *conservative* tweets about immigration, which is the issue area with the highest frequency of conservative tweets in the labeled dataset (Table 3). The lowest F1-scores occur for identifying *conservative* tweets about LGBTQ rights, which we attribute again to a very imbalanced dataset with few anti-LGBTQ messages.

Table 7 contains per-label, macro, and micro F1 scores for the *core framing task* and the *frame element* classifiers. Both models perform reasonably well, with the *core framing task* model achieving a micro-F1 score of 0.815 and the *frame element* model achieving a micro-F1 score of 0.763. As these results are substantially better than prior computational frame analysis work (Mendelsohn et al., 2021; Park et al., 2022), we consider our models to be sufficient overall for inferring framing strategies in the full corpus, and for conducting analysis with the inferred labels.

**Table 7: F1 scores for core framing tasks and frame elements.**

Core Framing Task	Dev F1	Test F1	Frame Elements	Dev F1	Test F1
Diagnostic	0.880	0.885	Problem ID (Diag)	0.856	0.869
Prognostic	0.761	0.765	Blame (Diag)	0.769	0.773
Motivational	0.657	0.690	Solution (Prog)	0.703	0.685
Macro F1	0.766	0.780	Tactics (Prog)	0.617	0.594
Micro F1	0.811	0.815	Solidarity (Prog)	0.773	0.777
			Counterframing (Prog)	0.398	0.473
			Motivational	0.662	0.697
			Macro F1	0.683	0.695
			Micro F1	0.758	0.763

At the same time, we observe variability in model performance across individual labels; some categories with lower performance are quite rare in the data. For example, the *core framing task* classifier has the lowest F1-score for *motivational* framing, which only appears in 14% of relevant labeled tweets (Figure 1), while 59% of relevant tweets contain *diagnostic* framing, the highest category. Indeed, F1 scores and support (number of labels in the evaluation set) are highly correlated, with Pearson correlation of 0.84 and 0.82 for all categories in the development and test sets, respectively.

When taking the imbalanced sample into account, model performance is even more encouraging. For example, *tactics* has a seemingly low F1-score of 0.594, but a random baseline classifier by comparison has in expectation an F1-score of just 0.191. Nevertheless, we decide to exclude stance and framing categories with F1-scores below 0.5 from further analysis in order to increase the reliability of our analysis. We thus omit the lowest performing frame element, *counterframing*. For all other categories, we infer labels on the full corpus. We first identify 1.48M (out of 1.85M) *relevant*, among which we identify *stance*, *core framing tasks*, and *frame elements*.

### Linguistic properties of core framing tasks

In our data annotation and classification tasks, we deconstruct social movement messages into core framing tasks and frame elements. These categories are still higher-order constructs which can themselves be decomposed into lower-level units, namely linguistic fea-

tures. Inspired by calls for more framing research to focus on such micro-level processes of meaning construction within texts (Johnston, 1995; Hedley and Clark, 2007; Vicari, 2010), we explore the linguistic features used to accomplish each core framing task. Beyond establishing that different core framing tasks are characterized by different linguistic markers, this analysis is primarily intended to give us a richer understanding of *how* authors communicate each core framing task, and thus offers a bridge between micro-level discourse analysis and higher-order content analysis approaches to social movement texts. From a computational perspective, such fine-grained linguistic analysis is also advantageous, as it offers a way to gain insights into our large-scale dataset and machine learning models. Linguistic features associated with messages containing each core framing task are also likely to be the same signals on which our models place high predictive weight in classification. As interpretability with large language models such as RoBERTa remains an open challenge, such linguistic analyses can provide insights into the models' decision-making process.

We identify linguistic features associated with each core framing task by calculating the log-odds ratio with informative Dirichlet prior within each issue area (Monroe et al., 2008). This metric identifies features that are statistically overrepresented in one corpus relative to another. For example, we compare the frequencies of linguistic features in *diagnostic* tweets about *immigration* to frequencies in all tweets about *immigration*. We calculate log-odds statistics for five linguistic features: words, verbs, adjectives, subject-verb pairs, and verb-object pairs. Our consideration of subject, verb, and object relations is inspired by Johnston and Alimi (2013), who argues that these structures are meaningful units for social movement frame analysis. We use the `en-core-web-sm` model in the SpaCy Python package for tokenization, part-of-speech tagging, and dependency parsing to extract subject-verb-object structures from tweets. For all features except words, we also preprocess features by lemmatizing (normalizing different morphological forms of the same words) with SpaCy. After calculating log-odds, we select the top 15 of each feature most associated with each core framing task within each issue area for qualitative analysis. We identify several themes that we will focus on for the remainder of this section, but the full log-odds results can be found in Appendix Table A3.

Patterns in **pronoun person marking** in the log-odds results suggest boundary framing processes that clearly identify protagonists and antagonists in conflict, literally

“us” vs. “them” (Snow et al., 1986; Vicari, 2010; Das and Whitham, 2021). For all issue areas, 3rd person pronouns (e.g., *they*, *their*, *he*) appear in the top 15 words most associated with diagnostic framing. Words most associated with prognostic framing include 1st person pronouns (e.g., *we*, *our*) and subject-verb tuples across issues include phrases such as *we need*, *we want*, and *we have*. Finally, 2nd person pronouns (e.g., *you*, *your*) are among the words most associated with diagnostic framing within immigration and LGBTQ tweets (while 2nd person pronouns are still significantly associated with motivational framing for gun tweets, it is crowded out by words from tweets motivating people to participate in gun giveaways and auctions). We further corroborate this relationship between pronoun person and framing with logistic regression models, which shows that diagnostic framing has the strongest positive association with 3rd person pronouns, prognostic framing is most associated with 1st person pronouns, and motivational framing is most associated with 2nd person pronouns (see Appendix Figure A1 for more details)

Qualitative analysis of the top 15 adjectives and verbs reveals the centrality of **moral language** in both diagnostic and prognostic framing. Across all issues, there are several adjectives most associated with diagnostic framing that express moral disapproval or disgust: *bad*, *sick*, *disgusting* for guns; *inhumane*, *cruel*, *evil*, *sick*, *wrong*, *disgusting* for immigration; *bad*, *wrong*, *disgusting*, *hateful* for LGBTQ. On the other end, top verbs associated with prognostic framing for all issues include deontic modal verbs such as *need*, *should*, and *must*, which often signal moral obligation (Vicari, 2010).

Closer analysis of verbs and their subject and object arguments provide additional insight into how movements deploy each core framing task, and commonalities across issue areas. For example, top verbs associated with diagnostic framing, such as *kill*, *attack*, *destroy*, and *murder*, suggest that violence is a commonly-identified problem. Perhaps less obviously, neglect is a commonly-identified problem across all issue areas, with verbs such as *fail*, *ignore*, *lie*, *refuse*, and *deny*. Messages from all issue areas engage in motivational framing by emphasizing the necessity of action (*need*, *do\_something*, encouraging readers to join a movement (*join*, *join\_today*, *join\_us*), and encouraging readers to pass or support legislation (*pass\_legislation*, *support\_bill*, *tell\_congress*)).

For all three issues, many of the same features are associated with each core framing

task, suggesting a degree of cross-issue stability and generalizability in how core framing tasks are linguistically constructed. However, analysis of individual words and verb-object pairs in particular reveal issue-specific components of core framing tasks. For example, Table A3 shows that some linguistic features are associated with diagnostic framing only within the *guns* issue area, such as *school*, *shooting*, *blame\_nra*, and *kill\_child*, while features associated with diagnostic framing for *LGBTQ rights* includes *homophobia*, *homophobic*, and *use\_slur*. Similarly, features associated with prognostic framing include *ban\_weapon* and *stop\_violence* for *guns*, but *celebrate\_pride* and *raise Awareness* for *LGBTQ rights*.

These findings highlight that log-odds ratios enable us to compare and contrast how the same core framing tasks are constructed across issue areas. These methods can be further applied to compare linguistic features of frames across axes beyond the issue area, such as ideological stance, time periods, and authors' social or professional identities. While largely beyond the scope of this work, we offer two brief examples. First, top features for diagnostic framing in progressive immigration tweets refer to the Trump administration family separation policy, such as *#trumpconcentrationcamps*, *#wherearethechildren*, and *separate\_child*. On the other hand, top features for diagnostic framing in conservative immigration tweets emphasize criminal activity, such as *illegally*, *break\_law*, *commit\_crime*, and *illegal\_vote*. Second, language associated with prognostic framing in progressive gun-related tweets largely focuses on the March for Our Lives demonstrations and emphasis on change (*marchforourlives*, *make\_change*, *find\_march*), while terms associated with prognostic framing in conservative gun-related tweets largely focus on preserving 2nd Amendment rights (*defendthesecond*, *protect\_right*, *defend\_2a*).

### **Frame variation across sociocultural contexts**

As social movements are situated within a broader time and space, their framing can shape—and be shaped by—social and cultural context (Snow et al., 1986; Benford and Snow, 2000). We address how framing varies across such contextual factors. We select three movement-level (issue area, stance, and protest activity period) and two message-level (author role and tweet type) dimensions for this analysis. We will first discuss our operationalization of each sociocultural factor, followed by Table 8, which summarizes each factor and its corresponding research question.

**Issue Area.** To broadly understand how social movement framing strategies vary across different contexts, we compare attention to each core framing task across the three issue areas included in our corpus: *guns*, *immigration*, and *LGBTQ rights*. We may expect to see higher rates of prognostic and motivational framing for *LGBTQ rights* because of the large number and size of Pride events in June. However, prognostic framing could also be more common for the other issue areas, as people may advocate for specific and concrete policy solutions for *guns* and *immigration*. While there have been long-sustained movements in all three issue areas, there were major offline events related to *guns* and *immigration* in this time period (the Parkland shooting and Trump's immigration policy, respectively) that could have implications for framing; for example, diagnostic framing could be most common for *immigration* if messages primarily express outrage at and criticisms of family separation. It is important to note that differences in framing strategies across issue areas may not necessarily be consequences of inherent properties of issues, as variation across issue areas may reflect differences in the nature of events and activities being discussed.

**Stance.** Although it may not necessarily be the case that each combination of stance and issue (e.g., *progressive* tweets about *immigration*) constitute a single social movement, comparing *progressive*, *conservative*, and *neutral/unclear* message framing could help us better understand the nature of movement/countermovement relationships. We expect both *progressive* and *conservative* tweets to be more likely to contain collective action frames compared to *neutral/unclear* tweets. However, it is not clear if there would be differences between *progressive* and *conservative* tweets in engagement with each core framing task.

**Protest activity.** We assess how attention to core framing tasks on Twitter varies between months characterized by *high protest activity* and *average protest activity* for each issue area. We expect that during periods of high protest activity, people would use Twitter to coordinate offline protests, discuss other tactics, and motivate people to participate, thus contributing to higher rates of prognostic and motivational framing during those periods. Note that while our dataset spans many different kinds of protest activities, ranging from Pride celebrations to school walkouts and marches, this analysis does not account for such differences in the nature of protest activity.

**Author role.** We compare framing across different author roles: *journalist*, *SMO*,

or *other* (mostly members of the public). Prior work has identified similarities in journalists' and activists' diagnostic frames on Twitter in the context of the 2014 Ferguson protests, but found that only activists tweet about protest action plans (Barnard, 2018). In their study of #MeToo, Xiong et al. (2019) argue that many hashtags used by SMOs are action-oriented, event-specific, and highlight specific activists. We thus may expect SMOs to engage in more prognostic and motivational framing. At the same time, many hashtags were also used for problem identification (Xiong et al., 2019), which could lead us to anticipate higher rates of diagnostic framing among SMOs compared to the other groups.

We identify journalists based on two existing lists of Twitter handles of journalists associated with major U.S. outlets (Tauberg, 2022; Gotfredsen, 2023).<sup>10</sup> We follow Bozarth and Budak (2022)'s procedure to identify SMO accounts. Specifically, the Crowd Counting Consortium data for most protest events includes the name of the SMO that organized the event. We then use the Twitter Search API to retrieve likely Twitter account matches for organizers of all protest events between 2017-2019 in any of the three issue areas. Out of 1.48M tweets classified as relevant, 4,218 are labeled with the *journalist* author role and 5,817 with the *SMO* author role. The remaining tweets are labeled with the *other* author role. Note that this mostly consists of tweets from the general public, but also includes content from citizen activists and politically-motivated users (Terechshenko et al., 2020).

**Tweet type.** We compare framing across different types of interactions on Twitter: *broadcasts* (original tweets), *quote tweets* (retweet with additional commentary), and *replies*. In contrast to *broadcasts*, both *replies* and *quote tweets* are responses to other messages. However, they differ in intended audience and communicative goals (Garimella et al., 2016); while *replies* are intended for the original post author and people engaged with the original post, *quote tweets* add commentary or additional context typically for a broader audience, including the quote tweeter's own network of followers. Prior work on discussions in a Swedish far-right Facebook group suggests that broadcasts may be more likely to identify problems, while replies may be more likely to assign blame and propose solutions (Wahlström et al., 2021); however, it is not clear if such patterns would generalize to our context of US-centered social movements on Twitter.

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<sup>10</sup>Data available at <https://github.com/taubergm/Top10000Journalists/tree/main> and <https://github.com/TowCenter/journalists-twitter-activity>

**Model.** We fit logistic regression models to analyze the relationship between framing and these five sociocultural factors. Sociocultural factors are included as independent variables, with the following reference levels: *guns* for issue area, *neutral/unclear* for stance, *average* for protest activity level, *other/public* for author role, and *broadcast* for tweet type. Because our stance labels come from classifiers with imperfect accuracy (and especially low performance for identifying anti-LGBTQ tweets), we additionally fit models that exclude stance. We model eight dependent variables: three core framing tasks (*diagnostic*, *prognostic*, and *motivational*) and five frame elements (*problem identification*, *blame*, *solution*, *tactics*, and *solidarity*). Each dependent variable is represented as a binary indicator representing the presence or absence of that framing strategy for a given message.

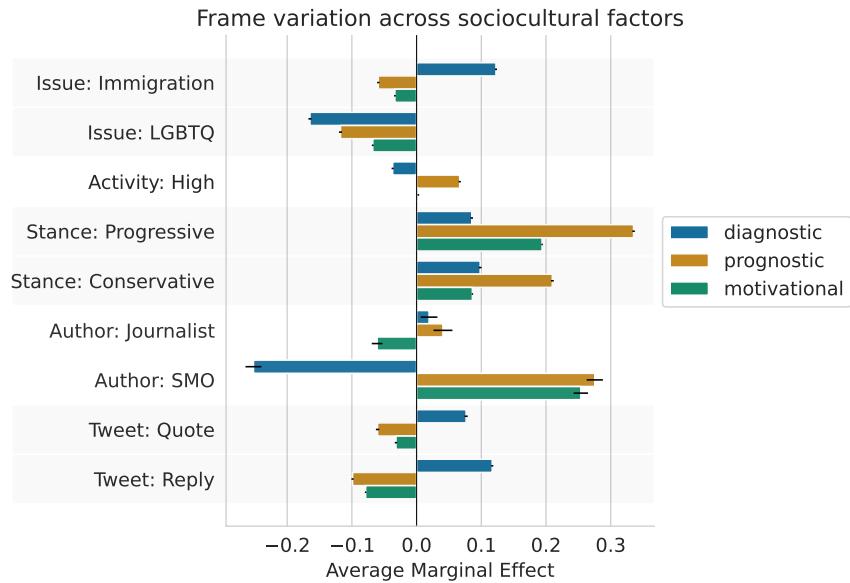
**Table 8: Sociocultural factors and their corresponding research questions**

Factor	Question
Issue Area	How does framing vary across three issue areas: immigration, guns, and LGBTQ rights?
Stance	How does framing vary between progressive, conservative, and neutral/unclear messages?
Protest activity	How does framing vary across tweets from high and average protest activity months?
Author role	How does framing vary between journalists, social movement organizations (SMOs), and others (neither SMOs nor journalists)?
Tweet type	How does framing vary across different types of Twitter interactions: broadcasts (original tweets), quote tweets (retweet with additional commentary), and replies?

### ***Sociocultural Factor Results***

Logistic regression results are shown in Figure 2 and Table 9. Results for models excluding stance are qualitatively similar (Appendix Figure A2 and Table A2). For ease of interpretability, we calculate the average marginal effects of each sociocultural factor for each core framing task. . The average marginal effect represents the average change in probability between the reference level and other values for each sociocultural factor, when all other independent variables are held constant.

*Issue area.* We see substantial cross-issue variation in framing. With all other variables equal, immigration-related tweets are 12.3% more likely to contain *diagnostic* framing than gun-related tweets but 5.9% less likely to contain *prognostic* framing and 3.4% less likely to use *motivational* framing. LGBTQ-related tweets are 16.5%, 11.8%, and 6.8% less likely than gun-related tweets to contain *diagnostic*, *prognostic*, and *motivational* framing, respectively. Table 9 suggests a more nuanced relationship between the issue and prognostic



**Figure 2. Association between sociocultural factors and framing tasks.**

*Note.* The x-axis shows average marginal effect estimates from the logistic regression models. Higher values represent stronger associations between sociocultural features and attention to core framing tasks. Error bars represent 95% confidence intervals.

framing in particular. While gun-related tweets are the most likely to contain *prognostic* framing overall, immigration-related tweets are the most likely to discuss *solutions*, and LGBTQ-related tweets are the most likely to express *solidarity* with a movement. While we identify systematic differences across issues, we do not explore the mechanisms underlying these patterns. While it is possible that there are inherent aspects to each issue that contribute to differences in core framing task usage, it is also possible that such variation is due to messages from different issue areas focusing on different types of events and activities.

*Stance.* Relative to tweets with a neutral/unclear stance, tweets with either progressive or conservative stances are much more likely to engage with any core framing task. Conservative tweets are slightly more likely to contain *diagnostic* framing than progressive tweets (9.8% vs. 8.5% increase in probability relative to neutral tweets), and particularly the *blame* frame element. Conservative tweets are less likely than progressive tweets to contain *prognostic* framing (21.0% vs. 33.5% increase in probability relative to neutral tweets)

and *motivational* framing (8.6% vs. 19.4% increase in probability). This analysis considers each of the core framing tasks separately. It appears that, overall, stance has stronger associations with core framing tasks than issue. This could be suggestive of alignment within stances (ideologies) in framing strategies across issues. We corroborate this finding with another operationalization, where we measure stance-based alignment by comparing stances in their *distribution* of framing strategies across issues, rather than considering each framing strategy individually (see Appendix for more details).

*Protest activity.* Figure 2 shows that compared to the other sociocultural factors, the protest activity level of the month when a tweet was written has a much weaker relationship with core framing tasks, although still in the expected direction. In months of high protest activity, tweets are 3.7% less likely to engage in diagnostic framing, 6.7% more likely to contain prognostic framing, and just 0.3% more likely to contain motivational framing. Table 9 breaks this down further: high protest activity months are less associated with *problem identification (diagnostic)* and *solution (prognostic)* frame elements, but significantly more associated with *tactics* and *solidarity* prognostic frame elements.

*Author role.* Figure 2 reveals substantial variation in framing strategies across author roles: whether an author is a journalist, SMO, or neither (which we call the “public”). Journalists are very similar to the public in their use of diagnostic and prognostic framing; in fact, in our regression models that exclude machine-labeled stance (Table A2), journalists are not significantly different in diagnostic and prognostic framing. Journalists are 6.1% less likely than the public to use motivational framing. Tweets written by SMOs pattern very differently. Relative to the public, SMO tweets are much less likely to use diagnostic framing (25.2%), and much more likely to use prognostic and motivational framing (27.5% and 25.4%). These effects are surprisingly large, with coefficient estimate magnitudes greater than those for any other sociocultural factor other than stance.

*Tweet type.* Finally, there is variation across tweet types. Compared to broadcast tweets, quote tweets and replies are more likely to contain diagnostic framing by 7.7% and 11.7%, respectively. Replies are 9.9% less likely to contain prognostic framing and 7.9% less likely to contain motivational framing than broadcasts. Quote tweets show the same pattern but with smaller differences: 6.0% less likely for prognostic and 3.2% less likely

for motivational. The smaller average marginal effects for quote tweets suggest that quote tweets have more in common with broadcasts than replies do.

**Table 9: Coefficient estimates from logistic regression models.**

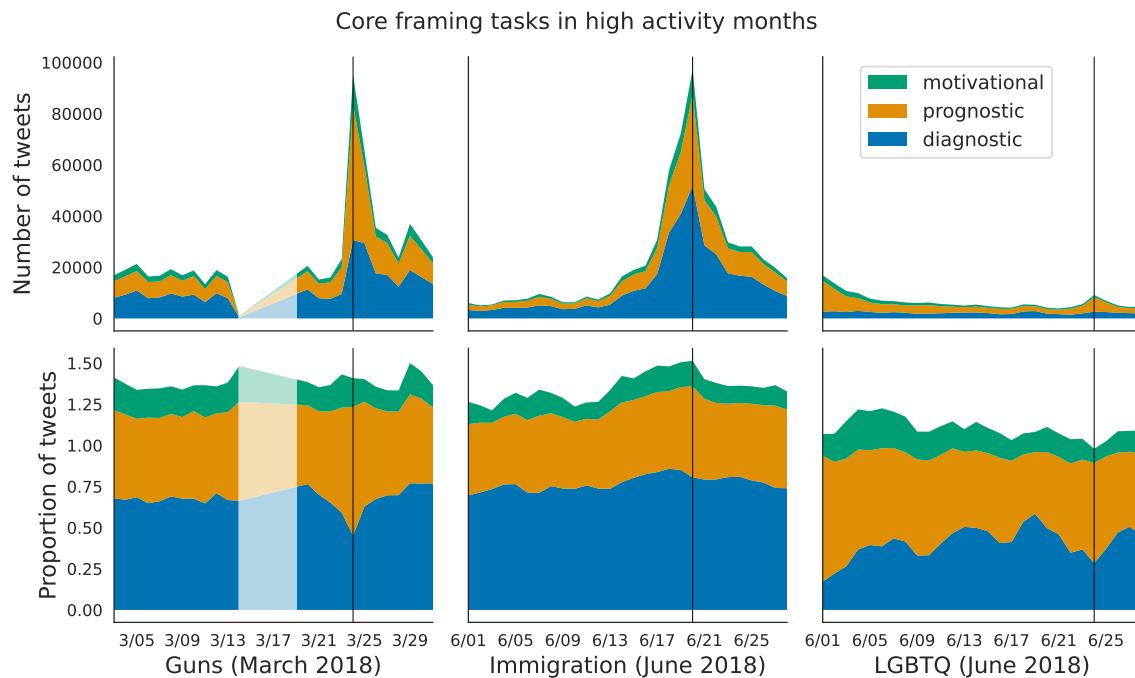
	Diagnostic	Prognostic	Motivational	Identify	Blame	Solution	Tactics	Solidarity
Immigration	0.629***	-0.261***	-0.280***	0.786***	0.498***	0.636***	-1.272***	-0.572***
LGBTQ	-0.703***	-0.518***	-0.627***	-0.369***	-1.144***	-1.343***	-1.791***	1.412***
Conservative	0.478***	0.922***	1.611***	0.357***	1.032***	0.907***	-0.141***	1.291***
Progressive	0.411***	1.445***	2.437***	0.389***	0.666***	1.015***	1.235***	3.152***
High Activity	-0.188***	0.291***	0.024***	-0.178***	-0.007	-0.133***	0.346***	0.676***
Journalist	0.098**	0.179***	-0.670***	0.223***	-0.007	-0.171***	0.264***	-0.319***
SMO	-1.143***	1.362***	1.560***	-0.974***	-1.099***	-0.078*	1.680***	0.185***
Quote	0.365***	-0.265***	-0.249***	0.201***	0.331***	0.089***	-0.478***	-0.497***
Reply	0.577***	-0.434***	-0.706***	0.479***	0.291***	-0.169***	-1.150***	-1.197***

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

*Note.* Columns represent dependent variables (core framing tasks and frame elements) and rows represent each sociocultural factor. Asterisks show significant coefficients relative to various thresholds after Holm-Bonferroni correction.

**Fine-grained temporal analysis.** The sociocultural factor regression analysis reveals surprisingly small framing differences between high and average protest activity months. There are several potential explanations for this result. Perhaps months is too coarse of a timescale to observe framing shifts during protests, which typically occur on a daily scale. Alternatively, maybe the relative attention to *diagnostic*, *prognostic*, and *motivational* framing strategies are truly stable over time regardless of offline protest. To better understand the relationship between time, framing, and protest, we analyze the distribution of core framing tasks for each issue area by day. Figure 3 shows temporal patterns for each issue area in their month of high protest activity (see Appendix Figures A3, A4, and A5 for daily temporal plots of high and average activity months side by side for each issue area).

Here we find evidence for both possible patterns. Within months, and even between low and high activity months, the distribution of *diagnostic*, *prognostic*, and *motivational* framing strategies remain remarkably stable across days. We observe increases in prognostic framing on days with protests, such as March 24, 2018 for *guns* and weekends in June 2018 for *LGBTQ rights* corresponding to major Pride events. Notably, not all spikes in Twitter activity are associated with frame distribution shifts. Unlike the other issues, the spike in activity for immigration does not represent a large collective action event, but rather public



**Figure 3. Daily framing task frequency for high protest activity months.**

*Note.* Time periods shown are March 2018 for *guns* (left), June 2018 for *immigration* (center) and *LGBTQ rights* (right). Raw counts of core framing tasks are shown in the top row and as a proportion of relevant tweets in the bottom row. The March for Our Lives demonstrations occurred on March 24, shown by the black vertical line in the leftmost plots. The line in the center plots at June 20 is when Trump signed an executive order ending family separation. The line in the rightmost plots occurs at June 24, the date of Pride parades in many U.S. cities including NYC, Chicago, and San Francisco. Note that the bottom plot does not sum to 1 because core framing tasks are not mutually-exclusive. The translucent gap from 3/14-3/19 is due to missing data from the Decahose stream. Plots also do not include 3/1-3/2 and 6/29-6/30 due to missing data.

outrage and a media storm surrounding family separation at the border. Even as volume exponentially increases during this storm, the balance of framing strategies remains stable. One notable exception to this stability is shown in Figure A5, which shows distributions of core framing tasks day-by-day for both high and average activity months (June 2018 and April 2019, respectively). During the high activity month, we see considerably higher rates of prognostic framing and lower rates of diagnostic framing for LGBTQ rights in comparison to guns and immigration. However, the average activity month has a much higher proportion of diagnostic framing, with the distribution more strongly resembling the other issues. The sustained increased prognostic framing throughout the entire high activity month, but only for LGBTQ rights, suggests that the distinct nature of Pride may shape our findings about both issue area and protest activity levels.

Finally, we ask: which stakeholder group is participating the most in these framing changes during protest days: journalists, SMOs, or the public? While we cannot fully answer this question due to much sparser data for journalists and SMOs, Figure A6 in the Appendix shows daily distributions of framing strategies for these groups. Interestingly, while SMOs generally engage in much higher levels of prognostic framing than the general public, their use of prognostic framing does not increase during protest days. Rather, SMOs increase their motivational framing in the days preceding major protests, such as March for Our Lives. We speculate that around these events, the division of labor shifts between movement actors: the general public (or perhaps rank-and-file activists) take on the work of prognostic framing, while SMOs focus on motivational framing and other movement activities beyond the symbolic dimension.

## Discussion

Framing is an active, dynamic, and contested process (Benford and Snow, 2000) that is not an inherent property of social movements. It develops through the assemblage of conversations between stakeholders such as activists, bystanders, opponents, organizations, and the media. In the digital age characterized by personalization and connective action (Bennett and Segerberg, 2011, 2012), where political action is more dispersed and decentralized (Kavada, 2016), it is important to consider the content, context, speakers, and audiences of individual messages in the study of framing (Earl and Garrett, 2017). Beyond challenging

earlier understandings of collective action, social media offers a unique window into understanding the development of social movement frames not just at the movement-level, but at the level of millions of individual messages (Kavada, 2016).

To better understand social movement mobilization on social media, we develop a computational approach to study collective action framing based on Snow et al. (1988)'s typology of *diagnostic*, *prognostic*, and *motivational* core framing tasks. By creating a codebook, a manually-labeled dataset of 6,000 tweets, and sophisticated machine learning models, we infer framing strategies for nearly two million tweets across three issue areas and multiple time periods. This approach enables us to conduct the empirical comparative work lacking in extant social movement scholarship, particularly in framing (Tarrow, 1996; Snow et al., 2014); our large-scale data facilitates analyses of frame variation not only across issues, but also stance, protest activity levels, author roles, and tweet interaction types.

Our analysis begins with an investigation into how tweets make use of lower-level linguistic resources to accomplish higher-level core framing tasks. While many linguistic features associated with each core framing task are issue-specific, we identify several consistent themes across all three issue areas. For example, we identify moral language to be prominent in both diagnostic and prognostic framing, and 3rd person pronouns to be highly associated with diagnostic framing, suggestive of boundary framing processes (Hunt et al., 1994). From the vantage point of computational methods, we reconstruct the centrality of collective ingroup identity in social movement discourse (Polletta and Jasper, 2001), drawing connections between social movement studies and social psychology for future work to further build upon. Beyond our analysis of linguistic features, our fine-grained temporal analysis of core framing tasks also reveals remarkable stability in the relative proportions of diagnostic, prognostic, and motivational framing strategies on a day-by-day basis. We hope future work further delves into this tension between the stability and dynamism of framing; what gives rise to such consistent patterns, and how can we reconcile these perspectives?

We then continue with an analysis of how framing varies across five sociocultural factors: issue area, stance, protest activity, author role, and tweet interaction type. Each part of this analysis speaks both to ongoing debates in social movement scholarship and sheds light on potential directions for future work. For example, our day-by-day temporal analyses

show shifts in relative proportions of each core framing task during protest days (i.e. *March for Our Lives* and *Pride parades*) but not during other notable but non-protest days with spikes in Twitter activity (i.e. in the (social) media storm surrounding family separation at the US-Mexico border). We do not know if this pattern generalizes across different types of offline events, and we do not attempt to determine if the type of offline event has any causal effect on online framing or vice versa. Nevertheless, these patterns highlight the potential—and a starting point—for further work to delve deeper into the connection between social media framing and offline events.

Our data provides us with a unique opportunity to understand the discursive construction of meaning in online social networks. We showcase these processes through our analysis of author roles and tweet types, highlighting that different kinds of participants and different kinds of interactions offer different kinds of meanings. While journalists and the general public engage with each core framing task to a similar degree, SMOs behave extremely differently, with far more *prognostic* and *motivational* framing than the other groups. Prior work has questioned and debated the relevance of SMOs in the digital age (Earl, 2015; Bozarth and Budak, 2021). While we cannot provide a definitive answer about the importance of SMOs based on this descriptive analysis alone, these substantial differences suggest that SMOs at least play a unique role in the online social movement ecosystem. Focusing on tweet types, we show that “broadcast” tweets are much more likely to cue prognostic and motivational strategies, while both replies and quote tweets are more likely to cue diagnostic strategies. This finding emphasizes that social media meaning-making occurs not through one-sided messaging, but through conversations, with each kind of interaction offering a unique contribution to the broader discourse. This analysis of tweet types begins to explore the relationship between framing and the affordances of social media platforms. Future research can unpack this relationship more: how do platform affordances affect collective action framing? Do differences in affordances across platforms shape how social movement mobilization strategies?

As this is solely a descriptive study, we do not attempt to make any arguments regarding framing effects. However, such description lays foundations for future research to address a broad range of causal questions. For example, what are the effects of exposure to diagnostic, prognostic, and motivational framing strategies? Does framing impact indi-

vidual audience members' participation in a social movement, or their perceptions of the movement's scope, efficacy, or necessity? Beyond perceptions, does framing actually affect movement participation and success? Especially given our finding that SMOs engage in more motivational framing immediately preceding protests, we may ask if framing drives protest activity. Future work could also measure if certain kinds of framing strategies tend to receive more engagement on social media (Mendelsohn et al., 2021). Higher engagement could be suggestive of stronger effects on audiences and lead to increased amplification by social media recommender systems, thus having major implications for the role of platforms in shaping social movement outcomes.

In addition to these directions for theoretically-motivated future work, we identify many opportunities for methodological innovation. We use a specific set of keywords to collect data from the Twitter 10% sample from just three issue areas, within which we consider only two months of activity from between 2018-2019. We do not know if our computational models or the patterns uncovered in our analyses are generalizable to other issues, time periods, or platforms. For example, do progressives always use more *prognostic* framing than conservatives? Or do we observe this pattern because progressive movements were more active in this time period, and may have been more likely to use Twitter for organizing? Do gun-related movements generally discuss *tactics* more than immigration-related movements, or is that merely a reflection of the fact that there were unprecedented demonstrations for gun control in 2018?

Particularly in light of Twitter and other platforms restricting data access for researchers and limiting opportunities for curating new social media datasets, this question is more urgent than ever: how can we ensure that the tools we build for large-scale social movement analysis work effectively for different movements, time periods, and platforms? We anticipate that transfer learning modeling approaches would be necessary here. While our dataset is limited, it contains three distinct issue areas each with two different months, and can thus provide a good testbed for future transfer learning model evaluation.

Future work may also consider integrating generative large language models (LLMs) such as ChatGPT into computational frame analysis. Recent work has considered LLMs as a tool to replace or augment human-provided annotations for many social science tasks

(Ziems et al., 2023), including news credibility rating (Yang and Menczer, 2023) and political affiliation prediction (Törnberg, 2023). In a set of data labeling tasks that closely resemble ours, Gilardi et al. (2023) finds that ChatGPT outperforms crowdworkers in labeling tweets about content moderation for relevance, stance, topics, media policy frames, and distinguishing tweets that frame content moderation as a problem vs. as a solution. However, the validity of LLM annotations has not yet been established in our domain of collective action framing on social media. Moreover, LLMs still perform considerably worse than trained experts for text annotation (Gilardi et al., 2023) and present additional concerns of reliability and consistency (Reiss, 2023). We suggest that LLMs should not be used in a fully unsupervised manner, but rather in collaboration with humans (Reiss, 2023; Ziems et al., 2023).

Theoretically, our descriptive study can serve as a foundation for future work to measure how framing strategies and frame *processes* (e.g. frame bridging, transformation, extension, and resonance) unfold through a complex, dynamic network of interactions on social media (Snow et al., 1986; Jost et al., 2018). This work opens avenues for empirical research to explore how framing affects political, cultural, biographical, and other dimensions of social movement success. Methodologically, we demonstrate the utility of computational methods for social movement content analysis and identify specific opportunities for computational techniques in subsequent research. As Snow et al. (2014) argue, “empirical investigations of framing hold the potential to influence activists’ practice toward greater efficacy in mobilizing recruits and gaining media attention”, suggesting that our work can hold direct implications for activist practices and strategies.

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## Online Appendix

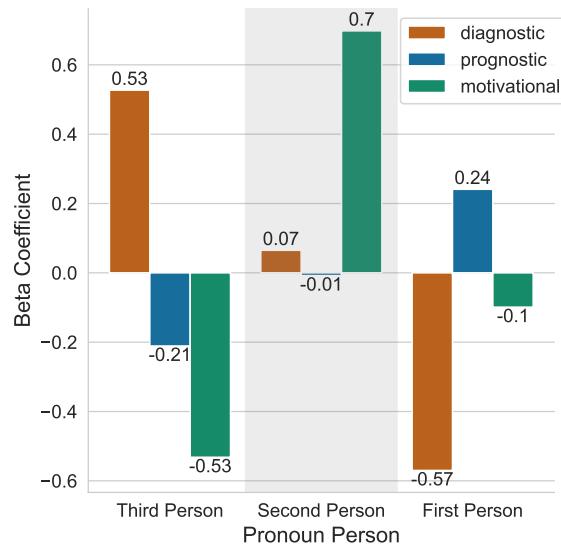
### *Model Performance*

**Table A1: Development F1-scores of stance classification**

Issue	Liberal	Neutral/Unclear	Conservative
Guns	0.731 (0.045)	0.539 (0.060)	0.631 (0.074)
Immigration	0.766 (0.015)	0.661 (0.041)	0.757 (0.013)
LGBTQ	0.855 (0.015)	0.588 (0.040)	0.183 (0.129)

*Note.* Separated by issue, averaged over five cross-validation folds. Standard deviation values are shown in parentheses.

### *Linguistic Analysis*



**Figure A1. Associations between core framing tasks and pronoun person.**

*Note.* The y-axis represents  $\beta$  coefficient estimates, where higher values represent stronger positive associations. Units of analysis are pronouns, dependent variables are pronoun person marking, and independent variables include issue area and whether the tweet in which the pronoun appears contains diagnostic, prognostic, or motivational framing strategies. Diagnostic framing is most associated with 3rd person pronouns, prognostic framing is most associated with 1st person pronouns, and motivational framing is most associated with 2nd person pronouns.

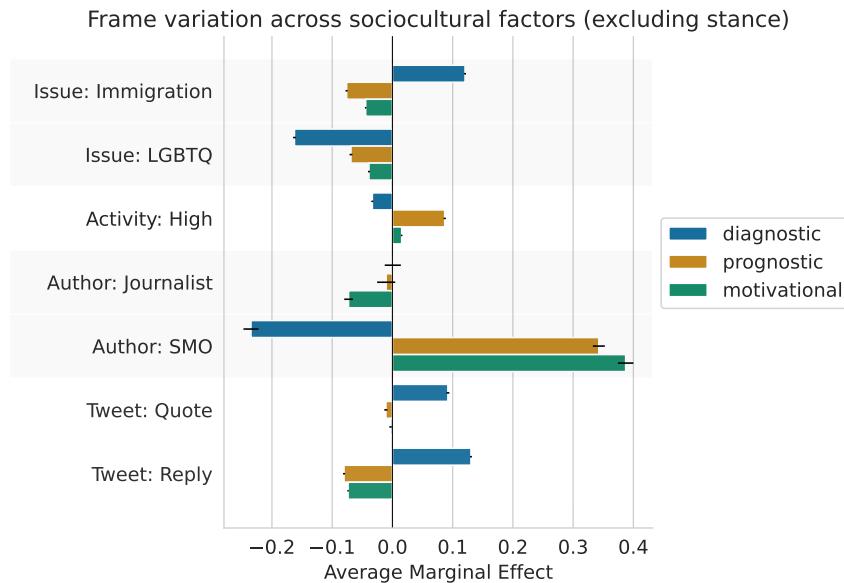
### *Sociocultural Factors*

**Table A2: Coefficients from logistic regression models excluding stance.**

	Diagnostic	Prognostic	Motivational	Identify	Blame	Solution	Tactics	Solidarity
Immigration	0.613***	-0.309***	-0.362***	0.767***	0.481***	0.587***	-1.289***	-0.660***
LGBTQ	-0.689***	-0.280***	-0.313***	-0.338***	-1.178***	-1.246***	-1.402***	1.734***
High Activity	-0.168***	0.353***	0.131***	-0.157***	0.008*	-0.087***	0.425***	0.788***
Journalist	0.003	-0.042	-0.814***	0.146***	-0.210***	-0.344***	0.224***	-0.441***
SMO	-1.058***	1.716***	1.967***	-0.879***	-1.015***	0.148***	2.072***	0.732***
Quote	0.435***	-0.044***	-0.022**	0.264***	0.468***	0.251***	-0.332***	-0.303***
Reply	0.638***	-0.327***	-0.638***	0.520***	0.453***	-0.052***	-1.187***	-1.211***

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

*Note.* Columns represent dependent variables (core framing tasks and frame elements) and rows represent each sociocultural factor. Asterisks show significant coefficients relative to various thresholds after Holm-Bonferroni correction.

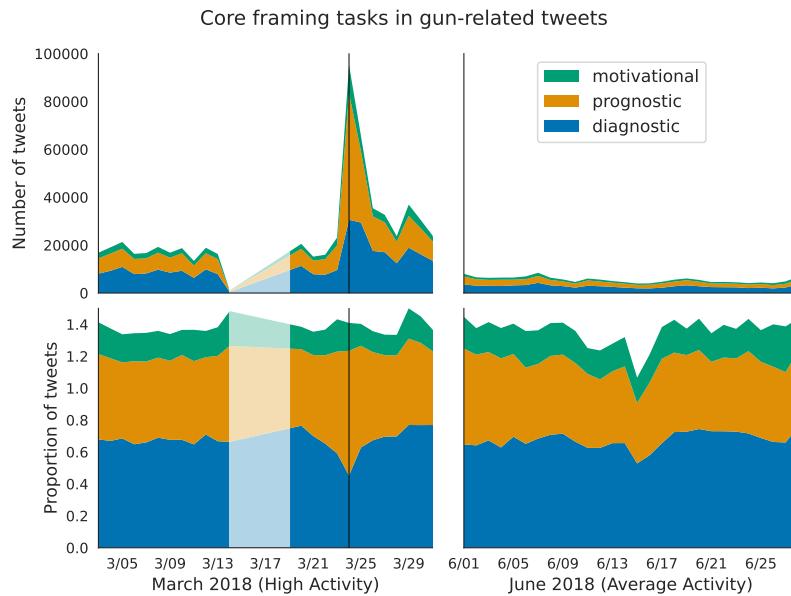


**Figure A2. Associations between sociocultural factors and core framing tasks excluding stance.**

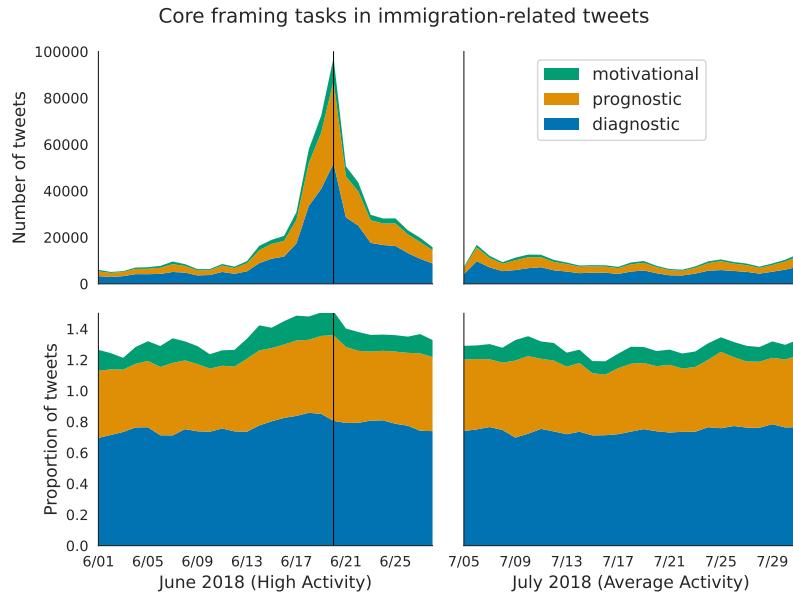
*Note.* The x-axis represents average marginal effect estimates for each factor from the logistic regression models. Higher values represent stronger associations between sociocultural features and attention to core framing tasks. Error bars represent 95% confidence intervals.

Given our findings from issue area and stance, we further ask: are ideologically-

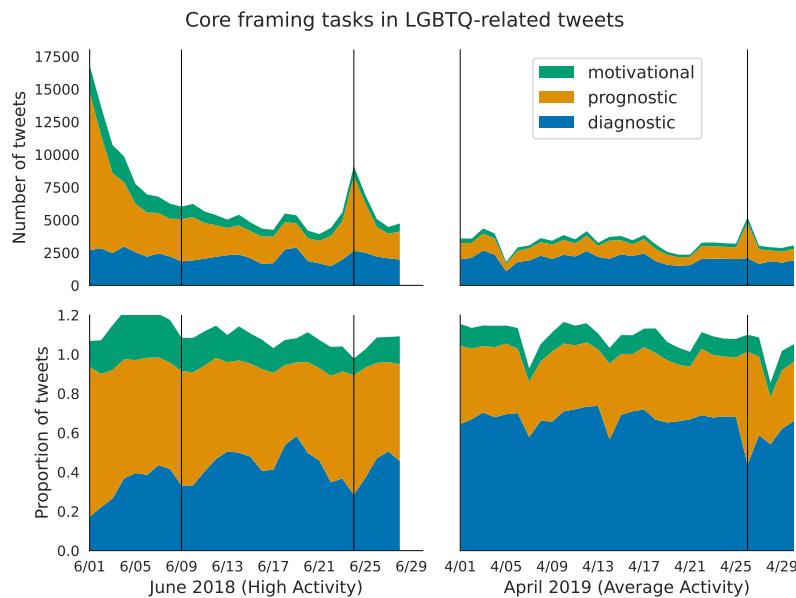
similar messages from different issue areas more aligned in framing strategies than ideologically-opposed messages from the same issue area? We answer this by calculating the pairwise relative entropy of the distributions of core framing tasks and frame elements between four groups of tweets: progressive gun-related, conservative gun-related, progressive immigration-related, and conservative immigration-related (we exclude LGBTQ-related tweets from this analysis due to the low performance in detecting anti-LGBTQ tweets). Lower relative entropy between two groups means that their distributions of framing strategies are more similar, and thus have greater frame alignment. We calculate entropy using 1,000 bootstrapped samples of 10,000 tweets each. We find that alignment is highest (i.e. lowest entropy) in framing across issues within the same ideology (progressive = 0.049, conservative = 0.052) and lowest between opposing ideologies within the same issue area (guns = 0.09, immigration = 0.097)



**Figure A3.** Core framing tasks per day for guns.

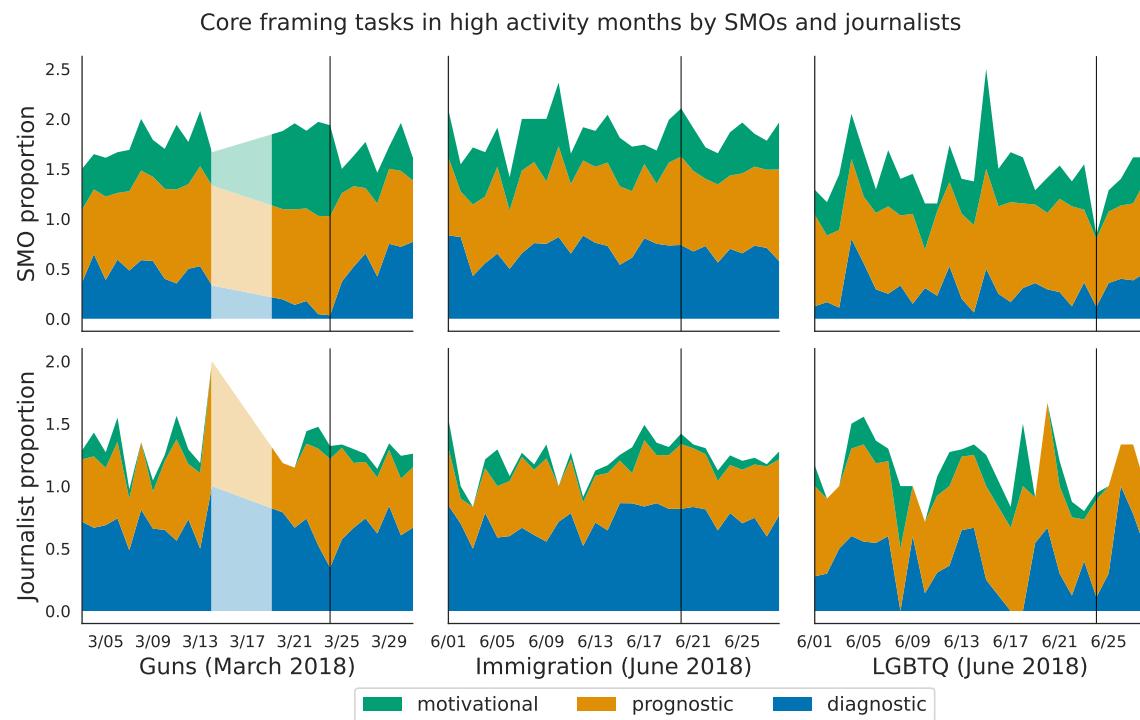


**Figure A4.** Core framing tasks per day for immigration



**Figure A5.** Core framing tasks per day for LGBTQ rights.

*Note.* Vertical lines in June 2018 represent days with many Pride parades. The vertical line at April 26, 2019 represents Lesbian Visibility Day.



**Figure A6.** Core framing task frequency per day in high activity months for journalists and social movement organizations (SMOs).

**Table A3: Top 15 linguistic features for each core framing task by issue.**

	Diagnostic			Prognostic			Motivational		
	Guns	Immigration	LGBTQ	Guns	Immigration	LGBTQ	Guns	Immigration	LGBTQ
Words	shooting	children	homophobic	marchforourlives	stop	pride	stop	please	please
	school	separation	homophobia	march	keepfamilies-together	happy	backfiretrump	stop	twibbon
	they	illegally	anti	today	should	[rainbow emoji]	bloodshed	join	help
	fatal	parents	that	stop	buildthewall	support	suffering	sign	add
	after	their	people	we	we	help	potus	your	support
	suffering	trump	they	neveragain	need	twibbon	fatal	petition	now
	backfiretrump	stop	racist	gun	to	month	m14	you	pastel
	that	policy	is	backfiretrump	abolishice	add	today	help	bisexual
	bloodshed	separated	not	control	wall	please	entered	familiesbe-longtogether	lgbt
	stop	kids	he	bloodshed	must	now	jra	stand	pride
Verbs	is	is	hate	suffering	deport	love	@sootch00	need	stop
	he	democrats	against	potus	end	pastel	longguns	call	a
	killed	child	do	vote	keepfamilies-together	winagun	@moveon	join	
	their	they	transphobia	change	thank	bisexual	guncontest	support	your
	potus	trumpconcentrationcamps	n't	our	worldrefugeeday	[green heart]	@classicfirearm	portman	our
	kill	separate	be	stop	stop	help	stop	stop	help
	suffer	stop	do	suffer	should	support	suffer	join	add
	stop	kill	hate	march	need	add	longgun	need	support
	shoot	cross	say	vote	must	celebrate	winagun	help	stop
	attack	break	call	need	thank	love	enter	sign	join
Adjectives	die	blame	stop	thank	join	thank	unsubscribe	stand	let
	blame	lie	misgender	ban	help	join	sign	donate	check
	lose	rip	refuse	join	end	need	join	demand	click
	murder	refuse	kill	should	abolishice	stop	need	support	need
	be	enter	attack	will	sign	hope	vote	must	epub
	bully	commit	homophobic	sign	worldrefugeeday	fight	let	elect	learn
	do	lose	should	support	build	should	register	let	donate
	try	destroy	use	protest	demand	share	stay	please	spread
	fail	care	deny	end	resist	will	dreamgun	wake	visit
	ignore	force	defend	fight	stand	donate	theme	read	sign
Subject-Verb	fatal	bad	homophobic	fatal	safe	happy	fatal	vulnerable	pastel
	unarmed	racist	anti	proud	buildthewall	proud	guncont	dear	more
	black	inhumane	racist	enough	well	amazing	sweet	historic	free
	bad	cruel	transphobic	young	open	beautiful	involved	more	excellent
	mass	illegal	bad	common	simple	pastel	official	@cbp	new
	dead	criminal	lgbt	safe	familiesbe-longtogether	great	vast	safe	online
	white	evil	sexist	amazing	great	safe	strong	@redomobile	sissy
	innocent	sick	white	sensible	proud	wonderful	enough	current	hashtag
	mental	wrong	wrong	powerful	full	inclusive	young	inhumane	safe
	sick	dangerous	religious	strict	adequate	important	@libertymutual	immigrant	available
Verb-Object	violent	disgusting	disgusting	strong	healthy	more	dear	urgent	next
	illegal	human	misogynistic	beautiful	strong	excited	common	analytic	criminal
	disgusting	innocent	gay	more	humane	awesome	preventable	reunite	important
	dangerous	homeless	hateful	great	more	happypride-month	ashamed	@rpfranceue	open
	russian	dead	violent	gunreformnow	executive	fallow	near	@speakerryan	civil
	potus_stop	they_want	i_hate	potus_stop	we_need	i_love	potus_stop	we_need	we_need
	police_shoot	they_care	you_say	we_need	future_await	we_need	i_enter	i_sign	mobi_epub
	texas_suffer	what_happen	they_re	reply_stop	we_want	we_celebrate	dreamgun_longgun	people_elect	you_need
	they_want	democrats_want	i_understand	i_sign	letter_	i_hope	reply_stop	we_elect	you_want
	people_die	they_break	that_	i_march	i_sign	we_love	texas_suffer	you_reverse	people_need
Verb-Object	ohio_suffer	who_break	i_agree	we_want	they_need	mobi_epub	we_need	million_want	you_like
	who_lose	who_cross	he_	i_support	we_elect	i_vote	ohio_suffer	refugee_deserve	you_help
	police_kill	you_care	brunei-implement	voice_hear	people_elect	we_stand	we_register	us_do	you_do
	illinois_suffer	you_break	who_think	texas_suffer	i_stand	i_support	illinois_suffer	you_do	's_keep
	who_survive	immigrant_kill	you_homophobic	i_stand	problem_solve	we_have	voice_hear	you_need	you_stop
	that_kill	they_try	they_do	we_march	globalcompact-migration_reflect	everyone_have	marchforourlive_unfold	you_help	you_join
	they_care	this_happen	he_do	we_register	refugee_deserve	people_need	i_sign	parliament-indicate	you_have
	nra_own	illegal_kill	they_hate	ohio_suffer	swiftdonate	california_suffer	pls_act	we_do	
	that_protect	dem_want	they_think	illinois_suffer	we_support	louisiana_suffer	you_join	i_urge	
	california_suffer	it_i	you_hate	we_have	you_reverse	racists_homophobic	you_have	we_celebrate	
	stop_bloodshed	break_law	have_right	stop_bloodshed	thank_you	add_twibbon	stop_bloodshed	sign_petition	add_twibbon
	kill_people	cross_border	use_slur	thank_you	build_wall	support_pride	winagun_m14	elect_you	support_pride
	do_nothing	separate_child	say_thing	sign_petition	sign_petition	support_pastel	enter_contest	add_name	support_pastel
	take_money	separate_family	make_comment	end_violence	stop_separation	thank_you	sign_petition	join_portman	join_w
	shoot_man	take_child	hate_people	find_march	deport_they	love_you	find_march	stop_separation	try_something
	kill_kid	do_nothing	say_what	make_change	await_child	celebrate_pride	win_308abatan	take_action	pass_equalityact
	survive_shooting	use_child	have_problem	ban_weapon	thank_@hp	join_we	end_violence	do_something	show_love
	push_agenda	enter_country	refuse_service	save_life	use_tech	see_you	join_today	join_we	like_this
	kill_man	commit_crime	call_i	join_today	connect_they	try_something	winagun_ar15	join_i	support_border
	blame_nra	separate_kid	make_fun	stop_violence	end_separation	show_support	theme_rifle	tell_congress	tell_congress
	take_right	put_child	call_them	raise_age	keep_family	raise Awareness	win_flag	pass_amnesty	need_right
	stop_shooting	stop_separation	misgender_i	vote_they	elect_you	support_you	save_child	support_bill	spread_word
	doAnything	rip_child	_homophobia	pass_legislation	add_name	celebrate_pride-month	deserve_yourself	educate_yourself	
	save_child	separate_them	call_he	support_marchforourlives	secure_border	celebrate_diversity	pass_legislation	slam_door	make_homophobia
	kill_child	add_name	make_joke	watch_marchforourlives	take_action	spread_love	take_min	reverse_it	support_circle