

Motivational Framing in Networked Publics on Indian Social Media: A Case Study of #HindusUnderAttack

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Abstract

Social movements employ various strategies to disseminate information, build support for their cause, and mobilize masses to take specific actions. One key tactical tool is framing. We utilize grounded theory to identify narrative, motivational, and issue-specific topical frames used in a digital networked public propagated by the Hindu right-wing groups using #HindusUnderAttack on Twitter. We leverage pre-trained, finetuned RoBERTa models to identify the occurrence of each frame in the corpus. Relying on past works on the Hindutva movement, we build three hypotheses rooted in the use of motivational frames (i.e. calls to action). Our findings illustrate three critical insights into framing around #HindusUnderAttack: 1) politically aligned users deployed the motivational frame more frequently, 2) tweets about Bangladesh are more likely to contain motivational framing, and 3) motivational framing is associated with higher audience engagement through retweets. We also report important patterns of frame combinations. Finally, we situate our findings in the political economy of the region and extant literature of digital publics around the world.

Introduction

The third consecutive election victory of Prime Minister Narendra Modi's Bharatiya Janata Party (BJP) in 2024 has firmly established Hindutva as a mainstream ideological brand in Indian politics. In online Hindutva discourse, framing has played a significant role in shaping narratives of Hindu victimization. A networked digital space that encapsulates this trend is #HindusUnderAttack. This thematic frame invokes a sense of collective identity and urgency — drawing on historical references, contemporary incidents, and perceived threats — to construct an image of collective victimization of Hindus. This includes allegations of bias against Hindus in the mainstream media, and government institutions like the police, the ruling party, and the judiciary. By studying how different actors engage in the framing process, we build on past literature to examine how identity-driven narratives of victimization intersect with the political economy of the region within the distinct and under-examined Indian context.

We use data collected from the X (formerly Twitter) public API with the search query #HindusUnderAttack from

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January 2020 to December 2022. Our analytical pipeline consisted of a four-step process: (1) exploratory analysis of the dataset, (2) coding of tweets to define and identify frames through grounded theory, (3) automated binary classification of the entire corpus of tweets for each frame, and (4) statistical modeling to characterize the relationship between framing, partisan identity, and user engagement.

We validated three hypotheses: that motivational frames are more likely to be used by BJP-supporting accounts, that tweets about Bangladesh are more likely to contain motivational framing, and that motivational frames receive higher amplification through retweets on Twitter. Additionally, we document common frame combinations such as the use of thematic frames alongside Hindu-victim and Muslim-antagonist frames, and the deployment of motivational framing in episodic and gender-based tweets. Through these findings, we illustrate a pattern of use that indicates the potential for motivational frames to serve a utilitarian purpose for the Hindutva movement in India, given that they receive higher amplification on Twitter/X. They also show the potential strategic impetus motivational framing has in national and provincial politics. Moreover, our findings provided quantitative and statistically significant evidence to validate prior research (Nandy 2019; Shamshad 2017; Jha and Chakrabarty 2023; Datta 2022; Sufian 2022) on the weaponization of Bangladesh as means of political mobilization and electoral campaigning in India.

By focusing on framing as a conceptual lens, this research contributes to broader discussions on social movements in the digital age in the Global South. Understanding how frames are constructed, adapted, and contested in online multi-lingual environments provides new insights into the mechanisms through which social movements influence public debate. Furthermore, our study shows the need for interdisciplinary approaches that integrate computational techniques with theoretical perspectives from sociology, communication studies, and political science, especially in scholarship of online communities in the Global South.

Background

The Hindutva (Hindu nationalist) movement emerged in the early 20th century as a vision of cultural nationalism distinct from religious Hinduism, emphasizing a unified iden-

tity against foreign influence. It shaped the creation of the Rashtriya Swayamsevak Sangh (RSS), a volunteer organization promoting Hindu cultural revival and political mobilization (Andersen and Damle 1987). Hindutva had limited political influence after India's independence in 1947 (Sangh 2019; Jaffrelot 1996; Dasgupta 2019). However, the BJP's rise in the 1990s reflected its success in linking Hindutva with development-oriented appeals to middle-class and urban voters (Jaffrelot 2007). The 2014 elections marked the movement's political consolidation, with Narendra Modi (himself an RSS volunteer) leading the BJP to its first parliamentary majority. Modi's 2019 and 2024 re-elections confirmed the mainstreaming of Hindutva in Indian politics.

Hindutva groups and the BJP have actively used social media, with Modi's campaigns bypassing mainstream press filters and outpacing the opposition in digital engagement during the 2014 and 2019 elections (Pal and Panda 2019; Panda et al. 2020a,b; Sharma 2022). Online discourse often depicts Hindus as victims of Muslims and other outgroups (Jain, Alavi, and Sharma 2024; Malji and Raza 2021; Shamshad 2017; Nath and Ray 2024; Nandy 2019; Sarma and Hazarika 2023). Three recurring frames dominate this space: *Hindu-victimization*, *gender-based threats* (notably "love jihad"), and *Muslim-antagonism*.

The Hindu-victim frame builds solidarity by portraying collective suffering (Dunn 2004; Stein 1998), often citing specific incidents to emphasize ongoing oppression (Isiaka 2022; Lee and Jang 2024; Zhang et al. 2023b; Chebrolu et al. 2024). Gendered narratives, particularly "love jihad," portray Hindu women as vulnerable and Muslim men as aggressors, reinforcing patriarchal and communal divides while mobilizing support through social media (Jain, Alavi, and Sharma 2024; Bhatia 2022; Gangopadhyay 2010; Smears 2019; Khalid 2024; Mukherjee, Shah, and Dexter 2023).

The Muslim-antagonist frame positions Muslims as existential threats, simplifying political conflict into a clear adversary (Mendelsohn et al. 2024; Datta 1993; Cherian 2023; Sian 2013). This narrative is especially salient in border states like Assam, where anti-immigrant sentiment merges with hostility toward Muslims (Datta 2022; Jha and Chakrabarty 2023; Sarma and Hazarika 2023; Malji and Raza 2021). Our analysis focuses on these three frames: *Hindu-victim*, *gender-based*, and *Muslim-antagonist*.

Related Work

Framing in Social Movements on Social Media

The role of framing in social movements has been extensively studied, particularly in the context of digital platforms that enable decentralized participation in political discourse (Mendelsohn et al. 2024; Li et al. 2021; Pan et al. 2023). Unlike traditional media, where elites and institutional actors dictate narratives, social media facilitates bottom-up frame construction by activists, party members, supporters, and even adversaries (Chebrolu et al. 2024; Lee and Jang 2024). In this study, we focus on the use of motivational framing, two types of narrative frames, and their occurrence alongside three issue-specific frames derived from the data.

Motivational Framing Motivational framing, as conceptualized by Benford and Snow (2000), constitutes a core element of the collective action frame alongside diagnostic and prognostic framing. While diagnostic frames define the problem and assign blame, and prognostic frames outline solutions, motivational frames serve as the emotional engine that drives individuals toward participation. They articulate the rationale for action by appealing to urgency, identity, and moral obligation. Stein (1998) argued that such frames often draw upon historically grounded injustices to foster a sense of moral urgency and group cohesion. Similarly, Dunn (2004) emphasized the use of "victim repertoires" that justify collective action through appeals to empathy and shared grievance. Motivational framing is thus particularly powerful in high-stakes political or identity-based campaigns, where calls for action hinge on deeply embedded emotional narratives.

A growing body of research highlights that motivational frames are disproportionately used by organizational actors like NGOs, political parties, and advocacy networks, compared to unaffiliated individuals (Brown and Harlow 2021; Xiao et al. 2022). These entities often have strategic communication objectives and are better resourced to craft persuasive messages that include explicit calls to action. Mendelsohn et al. (2024) found that movement organizations are far more likely to deploy motivational content compared to individual users. Their findings resonate with Brown and Harlow (2021), who analyzed protest messaging on Facebook and observed that posts with motivational frames originating from organizational pages elicited significantly more engagement. Additionally, Lou et al. (2024) suggest that motivational messaging can be more persuasive when it comes from actors perceived as credible or authoritative within the social movement network. This aligns with earlier work by Snow et al. (1986), who emphasized the role of resource mobilization and frame alignment processes in the success of collective action. This motivates one of our hypotheses i.e. that users inclined toward political organizations (e.g. the BJP) are more likely to use motivational framing.

Beyond organizational goals, motivational frames also play a central role in enhancing audience engagement metrics such as likes, shares, comments, and retweets (Thainiyom 2014; Li et al. 2021; Miri et al. 2024; Mendelsohn et al. 2024). Studies consistently show that content framed with motivational appeals, especially those that blend emotional tone with specific calls for justice or solidarity, achieves broader reach and interaction. For example, Li et al. (2021) demonstrated that tweets in the Chinese #MeToo movement which included motivational appeals had far greater diffusion than purely informational or diagnostic tweets. Likewise, Miri et al. (2024) conducted experimental research showing that emotional and motivational content was more likely to be shared due to its perceived urgency and affective impact. Motivational framing not only amplifies content visibility, but also deepens user investment and catalyzes digital activism (Lou et al. 2024). This is critical in networked publics, where the success of campaigns is often judged by user engagement and the viral potential of calls to action. Whereas past studies have

considered framing in the Western context or in China, our study extends this field by exploring comparable patterns of framing and audience response to it in the Indian context.

Narrative Frames Narrative framing relies on the distinction between episodic and thematic framing (Iyengar 1994), which influences the presentation of social issues. Episodic frames focus on specific individuals, events, or localized instances of broader problems, often using personal stories or real-time developments to engage audiences (Das et al. 2024; Li et al. 2021; Mendelsohn, Budak, and Jurgens 2021). Thematic frames, by contrast, present issues in a broader context, linking individual events to systemic or structural factors (Zhang et al. 2023b; Pan et al. 2023). Das et al. (2024) examine event-centric narrative structures, showing how episodic frames heighten engagement by evoking immediate emotional responses, while thematic frames create lasting cognitive impressions. Li et al. (2021) find that the #MeToo movement leveraged episodic framing by amplifying personal stories of sexual harassment, while also incorporating thematic frames that emphasized structural gender inequality. These studies indicate that movements strategically combine episodic and thematic frames to generate both short-term engagement and long-term awareness.

Research Questions and Hypotheses

This study examines the role of motivational framing in the #HindusUnderAttack discourse on Twitter, with particular attention to both the conditions under which such frames are deployed and the ways audiences respond to them. Motivational frames are of interest because they do not merely describe grievances, but actively encourage collective interpretation, mobilization, or action (Li et al. 2021; Miri et al. 2024; Thainiyom 2014). Prior work on political communication and digital mobilization suggests that such frames are often strategically employed by organizational actors (Brown and Harlow 2021; Xiao et al. 2022) and may be especially salient in contexts involving inter-group conflict (Li et al. 2021; Stein 1998; Dunn 2004). We organize this analysis around two research questions, the first of which motivates three testable hypotheses.

RQ1: *How are motivational frames deployed within the #HindusUnderAttack discourse on Twitter, and how do audiences respond to them?*

This question centers the analysis on both the production of motivational framing and its reception, providing a unifying framework for the three hypotheses that follow.

First, we examine the relationship between partisan identity and the use of motivational frames. Researchers have shown that users with organizational affiliations are more likely to deploy motivational frames to maximize engagement as well as to build support for their demands (Xiao et al. 2022; Miri et al. 2024; Brown and Harlow 2021; Mendelsohn et al. 2024). Moreover, motivational frames serve a strategic purpose in the context of electoral politics by linking an issue to a demand for action (such as voting). The BJP is the largest organization in the socio-political universe of the Hindutva movement and has actively leveraged

issues of Hindu victimization in election campaigns (Malji and Raza 2021). Therefore, we hypothesize that users who are politically engaged with the BJP are more likely to post tweets with motivational frames.

Hypothesis 1: *Twitter users with 'BJP' in their description are more likely to post motivational tweets*

Second, we consider the contextual conditions under which different frames are deployed. In particular, we are concerned with India's Muslim-majority neighbors – Pakistan and Bangladesh. Our interest in these two countries stems from their salience to the domestic political discourse in India. India and Pakistan have fought three major wars and several smaller conflicts since India's partition on religious lines in 1947. Pakistan remains a major issue even in domestic policy discussions as documented by analyses of social media campaigns in the 2019 general elections (Panda et al. 2020b; Pal and Panda 2019). However, in recent years, Bangladesh has also emerged as a major focal point regarding cross-border migration (Malji and Raza 2021; Sarma and Hazarika 2023). This was evident in the confluence of Hindu-Muslim polarization with the native-migrant divide in the provincial elections in Assam in 2021 (Jha and Chakrabarty 2023; Datta 2022; Sufian 2022).¹ Given prior findings on the domestic political economy of rhetoric surrounding Bangladesh, and the use of motivational frames in inter-group conflicts, we hypothesize that:

Hypothesis 2: *Tweets about Bangladesh are significantly more likely to contain motivational frames*

Third, we investigate how audiences respond to authors' framing preferences. On social media platforms, retweeting functions as a key mechanism of amplification (Muñoz-Expósito, Oviedo-García, and Castellanos-Verdugo 2017; Zhang et al. 2023a), allowing messages to reach broader audiences beyond their original network. Moreover, prior research indicates that emotionally and rhetorically charged content is more likely to be amplified (Brown and Harlow 2021; Li et al. 2021; Miri et al. 2024). Specifically, motivational tweets receive higher engagement from audiences (Miri et al. 2024; Lou et al. 2024). Therefore, we hypothesize that:

Hypothesis 3: *Motivational frames are positively associated with the likelihood of being retweeted*

Beyond these directional predictions, we also examine the co-occurrence of frames within individual tweets. Prior work has shown that social movements strategically combine frame types — for instance, pairing episodic frames with motivational ones (Li et al. 2021). Rather than predicting specific combinations, we treat this as an open empirical question:

RQ2: *Which frames are more likely to co-occur within individual tweets in the #HindusUnderAttack discourse?*

¹Assam is an Indian state that borders Bangladesh. The state language is Assamese and the issue of Bengali speakers migrating to the state has been contentious for decades (Datta 2022).

Data & Methods

Our dataset contains a random sample of tweets posted with the hashtag #HindusUnderAttack between January 2020 and December 2022. The data, collected by researchers at the University of Massachusetts Amherst, consists of 465K tweets in total, including over 82K unique tweets. We only included tweets in English (language-coded as ‘en’ by Twitter) and Hindi (hi) and tweets that mostly contained hashtags (qht) or mentions (qme). This reduced the size of our corpus to 63,156 tweets. Table A1 (in the appendix) shows a few examples of tweets in the corpus, including translations for the Hindi tweets.

Our evaluation of this dataset followed a four step process: (1) exploratory analysis of the corpus to identify topical categories, (2) manual coding of tweets into each of the six categories – two narrative, motivational, and three topical, (3) automated classification of all tweets in the corpus, and (4) analysis of tweet and retweet patterns.

Constructing the Typology of Frames

Our framing typology comprises six binary categorical variables: two narrative frames (episodic and thematic), three issue-specific frames (Hindu-victimhood, gender-based, and Muslim-antagonist), and the motivational frame. We developed this typology of frames using a grounded theory approach, iteratively analyzing a sample of tweets. We draw on established framing traditions in computational social science, including issue-generic, issue-specific, narrative, and collective action framing (Mendelsohn et al. 2024; Mendelsohn, Budak, and Jurgens 2021). Specifically, we examined an initial sample of 500 tweets and grouped emergent sub-categories to arrive at cohesive and conceptually consistent definitions for each frame. This process yielded six recurring frames: two narrative frames (episodic and thematic), one motivational frame, and three issue-specific frames, which can also be interpreted as diagnostic frames within the collective action framing tradition (Snow et al. 1986).

To refine the frame definitions and assess labeling consistency, the first and second authors independently annotated random samples of 100 tweets each across six iterative coding waves. After each wave, disagreements were discussed and definitions were refined. Inter-coder reliability was assessed after each round using Cohen’s κ , a measure of agreement for categorical data that accounts for random chance of agreement (Cohen 1960). Following conventional guidelines, κ values between 0.41–0.60 indicate moderate agreement, 0.61–0.80 substantial agreement, and values above 0.80 near-perfect agreement (Landis and Koch 1977).

After the final round of annotation, four of the six frames achieved substantial agreement: episodic ($\kappa = 0.78$), motivational ($\kappa = 0.79$), gender-based ($\kappa = 0.81$), and Hindu-victimhood ($\kappa = 0.78$). Agreement was lower for the thematic ($\kappa = 0.53$) and Muslim-antagonist ($\kappa = 0.67$) frames, reflecting the interpretive complexity of these categories. In the case of thematic framing, coders were required to assess whether diffused linguistic cues, such as hashtags, implicit generalizations, or loosely connected phrases, collectively constituted a broader theme rather than a reference to a specific event. Similar ambiguity arose for Muslim-antagonist

framing, particularly in tweets referencing public figures or using Hindi terms in *Devanagari* script where the Muslim reference was implied rather than explicit.

For these two frames, we adopted consensus coding between the two annotators to produce final labels using the definitions provided in the Appendix. While the κ scores for these categories are lower than for more concrete frames, they are comparable to those reported in prior work using grounded and iterative annotation approaches for abstract framing constructs (Mendelsohn et al. 2024).

Classification of Tweets

Following the process of defining frames, the first author labeled a separate random sample of tweets (N=1000) to construct a training set for our classifiers. This sample size is in line with prior research (Mendelsohn et al. 2024). Moreover, BERT-based classifiers are built to be finetuned with small samples. While the training labels are not labeled by both coders, we used the corpus from our initial sample for the test data. Therefore, the test data contains frame-labels that both coders agreed upon, and is much more reliable and generalizable. This meets the state-of-the-art methods in coding for frame-types (Mendelsohn, Budak, and Jurgens 2021). In the training sample, we observe high coverage rates for each frame type. In the labeled set, of 64.07% of tweets were episodic tweets, 47.56% were thematic tweets, 40.46% were motivational tweets, 10.56% were gender-based tweets, 45.20% were Hindu-victim tweets, and 47.82% were Muslim-antagonist tweets. It must be noted frames are not mutually exclusive, i.e. a single tweet may contain multiple frames.

To classify tweets into the six framing categories, we finetuned transformer-based binary classifiers using RoBERTa-base and XLM-RoBERTa-base. For each frame, we constructed a labeled dataset in which frame presence was coded as a binary outcome, with the positive class indicating frame occurrence. To reduce overfitting and ensure robustness, we employed stratified K-fold cross-validation (K = 5) within the labeled training data. In each fold, models were trained on four partitions and evaluated on the held-out fold, preserving the class distribution across splits. Fine-tuning was conducted for a maximum of thirty epochs with early stopping based on validation F1 score, gradient clipping, and learning-rate warmup. The best checkpoint in each fold was selected automatically using validation performance. After cross-validation, we trained a final model using the same configuration and evaluated it once on a held-out test set. This procedure allowed us to assess both within-sample stability via cross-validation and out-of-sample generalization via test set metrics, substantially mitigating concerns about overfitting.

Independent Variables

Our statistical models include six independent variables, spanning user-level and tweet-level characteristics. At the user level, we include three platform metrics: verification status, follower count, and total number of tweets posted. We also construct an indicator of partisan affiliation based on whether a user’s profile description contains the term

Categorical Variable	Definition	Inter-coder Reliability (κ)
Episodic	Mentions of specific people, events, places, or organizations	0.78
Thematic	Linking multiple events or making generalized claims	0.53
Motivational	Calls to action, demands, pleas, or requests	0.79
Gender-based	References to crimes against or harassment of women	0.81
Hindu-victimhood	Claims of victimization of Hindus	0.78
Muslim-antagonist	Portrayals of Muslims as antagonists or bad actors	0.67

Table 1: Inter-coder reliability scores (Cohen’s κ) for each frame after the final coding wave

Frame	CV F1 (mean \pm SD)		Test F1	
	RoBERTa	XLM-RoBERTa	RoBERTa	XLM-RoBERTa
Episodic	0.939 \pm 0.018	0.949 \pm 0.009	0.898	0.901
Thematic	0.873 \pm 0.022	0.888 \pm 0.015	0.750	0.839
Motivational	0.824 \pm 0.036	0.851 \pm 0.032	0.841	0.900
Gender-based	0.829 \pm 0.043	0.840 \pm 0.058	0.672	0.778
Hindu-victim	0.889 \pm 0.025	0.902 \pm 0.022	0.850	0.869
Muslim-antagonist	0.862 \pm 0.018	0.875 \pm 0.040	0.823	0.874

Table 2: Classification performance for RoBERTa and XLM-RoBERTa models. Reported are mean F1 scores across 5-fold cross-validation (with standard deviations) and F1 scores on an external held-out test set. Best-performing model per frame is shown in bold.

”BJP.” To validate this measure, we manually labeled a stratified sample of 200 user accounts—100 with “BJP” in their bio and 100 without—coding whether each user explicitly claimed support for or affiliation with the party. This procedure yields high accuracy and F1 scores (both 93.5%), indicating that the presence of ”BJP” in a user’s bio provides a reliable proxy for partisan identification. Among accounts classified as BJP supporters, 59% claimed formal affiliation or positions within the party, while an additional 34% expressed explicit support.

At the tweet level, we control for the language of the tweet and its geopolitical reference. Tweets containing the term ‘Bangladesh’ are coded as referencing Bangladesh, and those containing ‘Pakistan’ as referencing Pakistan (both matched in lowercase). These indicators are combined into a four-category variable capturing whether a tweet references Bangladesh, Pakistan, both, or neither.

Assessing Potential Bot Activity

To assess potential bot activity without relying on Twitter/X API data, we applied BotometerX (Yang et al. 2019), a language- and metadata-based model that estimates account automation. BotometerX outputs a continuous score between 0 and 1, with higher values indicating stronger signals of automation. Following prior validation work, botometer scores can be interpreted as follows: below 0.3 - human-operated accounts, 0.3 to 0.5 - ambiguous, 0.5 to 0.7 - suggestive of automation, and $>$ 0.7 - strong automation signals (Yang et al. 2019). Due to computational constraints, BotometerX was applied to a random 4% sample of accounts as a diagnostic of bot prevalence. Most accounts exhibit low automation likelihood. Approximately 55.7% of users score

below 0.3, with an additional 33.7% falling between 0.3 and 0.5. Only 9.3% of accounts score between 0.5 and 0.7, and just 1.36% exceed the 0.7 threshold. The mean BotometerX score is 0.28 (median = 0.27), suggesting that automated accounts are relatively rare and unlikely to drive the observed framing patterns.

Measuring Audience Response To gauge user response on Twitter/X, prior research has identified multiple engagement metrics, which can be broadly grouped into user-level attributes (e.g., follower count, posting activity, verification status) and activity-based measures (e.g., retweets, likes, replies, quote tweets) (Zhang et al. 2023a). Engagement itself can take several forms, including diffusion or amplification (e.g., retweets and cross-platform sharing), approval (e.g., likes and follows), and conversational interaction (e.g., replies, quotes, emoji reactions) (Muñoz-Expósito, Oviedo-García, and Castellanos-Verdugo 2017). While we include user-level attributes as control variables, we operationalize user response using retweets. This choice is motivated by two considerations. First, although likes, replies, and quote tweets are available in the data, replies and quotes do not necessarily signal endorsement, and likes are often used as bookmarks, making them a noisy indicator of support (Muñoz-Expósito, Oviedo-García, and Castellanos-Verdugo 2017). Second, because our analysis focuses on the potential virality of framed content, retweets provide a more direct and reliable measure of both endorsement and amplification on Twitter.

Statistical Modeling

Our first two hypotheses (**H1** and **H2**) consider the relationship of motivational framing with the user’s partisan-

ship and geo-political context, respectively. To this end, we estimate a logistic regression model where the dependent variable is a binary indicator of whether a tweet contains a motivational frame. Independent variables include indicators for user characteristics (verified status, follower count, and overall tweeting activity), linguistic features of the tweet (language), partisan affiliation, and topical context (references to Pakistan, Bangladesh, or both). Continuous covariates are log-transformed to reduce skewness, and categorical variables are entered as factor indicators. Coefficients are estimated using maximum likelihood, and results are reported as log odds coefficients with corresponding confidence intervals. We used the logistic regression model defined as below:

$$\begin{aligned} \text{motivational}_{i,j} \sim & \text{verified}_j + N_j^{\text{followers}} + N_j^{\text{tweets}} + \\ & \text{description}_j + \text{language}_i + \\ & \text{country_reference}_i \end{aligned} \quad (1)$$

The language values are aggregated into five categories in our analysis: English, Hindi, Hashtags, Mentions², and Other/Undefined.

To validate **H3**, which considers audience response to motivational framing, we assess the relationship between the frames contained in a tweet and the number of retweets it receives. For this we used the following linear regression model:

$$\begin{aligned} N_{i,j}^{\text{retweets}} \sim & \text{verified}_j + N_j^{\text{followers}} + N_j^{\text{tweets}} + \\ & \text{description}_j + \text{language}_i + \text{Episodic}_i + \\ & \text{Thematic}_i + \text{Motivational}_i + \\ & \text{GenderBased}_i + \text{HinduVictim}_i + \\ & \text{MuslimAntagonist}_i + \text{country_reference}_i \end{aligned} \quad (2)$$

In this model, the binary categorical variables *Episodic_i*, *Thematic_i*, *Motivational_i*, *Gender – based_i*, *Hindu – victim_i*, and *Muslim – antagonist_i* indicate whether tweet *i* contains those respective frames. Here too, continuous variables are log-transformed. We estimated coefficients using ordinary least squares, and report regression coefficients with 95% confidence intervals.

Finally, to examine how users combined frames within individual tweets (**RQ2**), we analyze pairwise frame co-occurrence using odds ratios derived from contingency tables. For each unique pair of frames, we estimate the odds ratio comparing the likelihood that the two frames appear together in the same tweet relative to appearing separately. Statistical significance is assessed using chi-square tests of independence, and report the 95% CI and p-values in our results.

²Twitter uses language codes ‘qht’ and ‘qme’ to label tweets that mostly or entirely contain hashtags and mentions respectively

Results

Examining the results from models 1 and 2, we find that all three of our hypothesis are validated i.e. motivational tweets are more likely to be used by BJP-supporting accounts, they are more likely to be used in tweets about Bangladesh, and they are associated with increased retweeting behavior. Moreover, our analysis of frame co-occurrence reveals that the following pairs were most likely to be combined in tweets: Hindu-victim/thematic, Hindu-victim/Muslim-antagonist, episodic/gender-based, and episodic/motivational. In this section, we start by detailing the results of frame labeling, descriptive findings, and statistical modeling.

Classification of Tweets

Table 2 shows the model performance results for the base RoBERTa and the multilingual RoBERTa models. Overall, the frame classification models achieved strong and stable performance across frames, supporting their use in subsequent analyses. Test-set F1 scores ranged from approximately 0.75 to above 0.90, with higher performance observed for episodic, Hindu-victimhood, and Muslim-antagonist frames, and comparatively lower—but still acceptable—performance for thematic, motivational, and gender-based frames. In line with prior work, frames requiring more contextual or interpretive judgment—particularly thematic framing—proved more difficult to classify than frames defined by more explicit lexical cues. Across frames, XLM-RoBERTa slightly outperformed RoBERTa on average, particularly for frames involving multilingual or transliterated content, and was therefore selected as the primary model for inference. The consistency between cross-validated and held-out test performance suggests limited overfitting and indicates that the automated labels reliably capture the framing patterns identified in the manual coding process.

Descriptive Findings

Figure 1 shows monthly counts of original tweets with the #HindusUnderAttack hashtag (N=63,156). Over 94% appeared after January 2022, with an early peak in October 2021. The figure also tracks monthly motivational framing.

Each spike corresponds to offline events that triggered X/Twitter discourse. In October 2021, about 2,500 tweets focused on attacks on temples and *mandaps*³ during *Durga Puja*⁴ in Bangladesh. Hashtags like #SaveBangladeshiHindus and #SaveHinduTemples dominated, with some tweets linking the issue to West Bengal politics and the AITC — the ruling party in the state of West Bengal and principal rival of the BJP.

The next peak in April 2022 followed communal clashes in New Delhi’s Jahangirpuri area during *Hanuman Jayanti*⁵.

³Mandaps: Tents or temporary structures erected during festivals, marriages, or cultural events

⁴Durga Puja: Ten-day festival in honor of Hindu goddess Durga

⁵Hanuman Jayanti: Festival marking the birth of the Hindu deity Hanuman

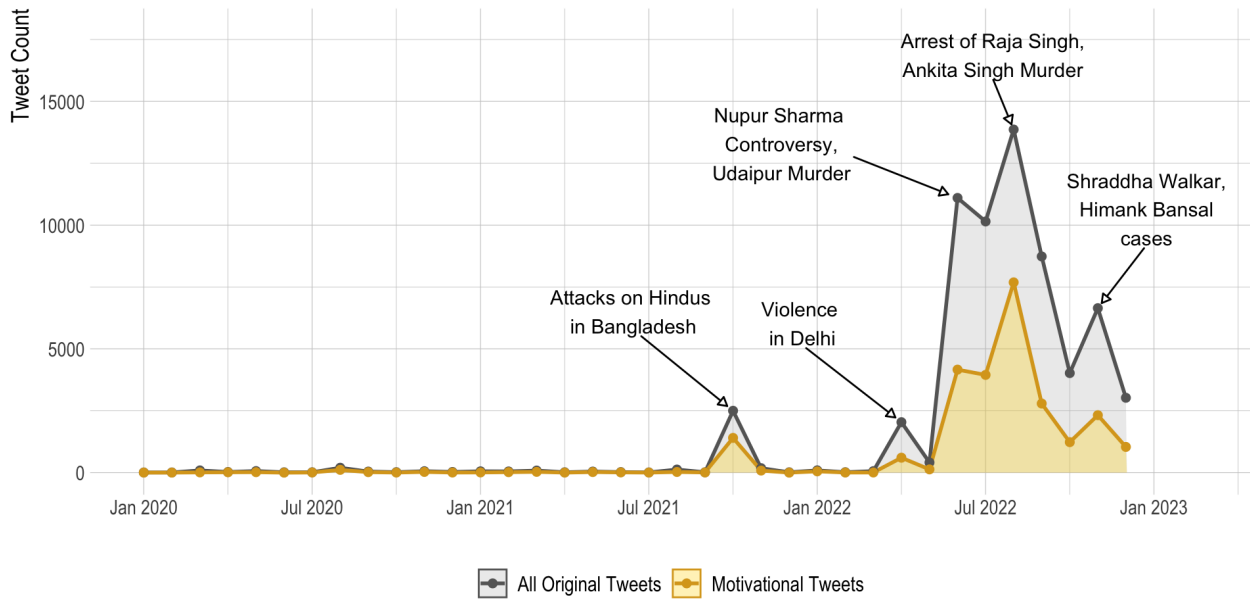


Figure 1: Timeline of tweets posted with #HindusUnderAttack (excluding retweets) and key events that triggered them

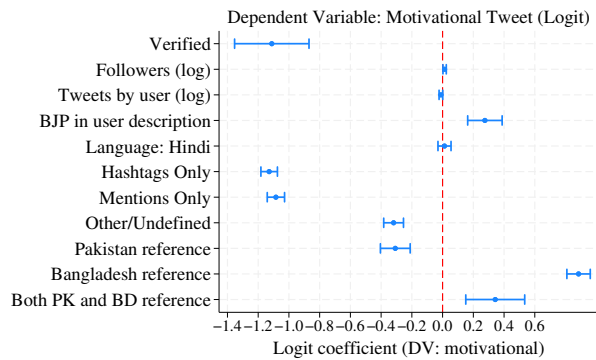


Figure 2: Coefficient plot from a logistic regression predicting the likelihood that a tweet contains a motivational frame. Points represent estimated log-odds coefficients and horizontal bars indicate 95% confidence intervals. Positive values indicate a higher likelihood of motivational framing relative to the reference category. The model includes user-level and tweet-level controls.

Popular hashtags included #HinduLivesMatter, #HinduPhobia, and motivational frames such as #HindusWakeUp and #HindusUnite. June 2022 saw the second-highest surge (N=11,099), driven by two events: outrage over BJP spokeswoman Nupur Sharma’s remarks about the Prophet of Islam, and the murder of Kanhaiya Lal — a Hindu man — in Udaipur. Tweets frequently used #ISupportNupurSharma and #JusticeForKanhaiyaLal.

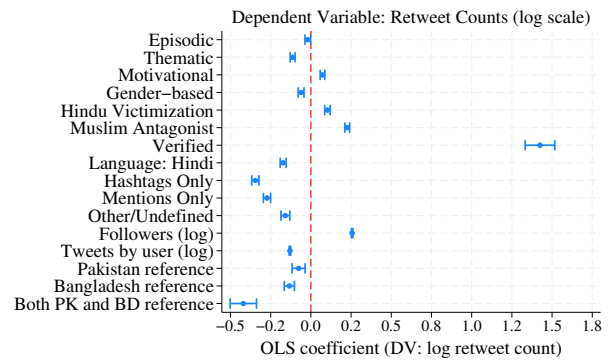


Figure 3: Coefficient plot from an OLS regression predicting log retweet counts. Points denote estimated coefficients and horizontal bars show 95% confidence intervals. Positive values indicate higher expected retweet counts, holding user- and tweet-level covariates constant.

The largest spike occurred in August 2022 (N=13,862), linked to BJP leader Raja Singh’s arrest and the killing of Ankita Kumari. Trending hashtags included #JusticeForAnkita, #SarTanSeJuda, and the critical #BJP_Fattu_Hai (BJP is cowardly). The final peak came in November 2022 (N=6,646), centered on the murder of Shraddha Walkar by her Muslim partner and the assault on Himank Bansal in Hyderabad.

Each of these cases illustrates the combination of frames in the construction of a victimhood narrative. Any analysis

of the online Hindutva discourse must consider the political economy and electoral implications of such frame selections. We discuss these in the Discussion section.

Results of Statistical Modeling

The results of our regression models validate all three of our Hypotheses. Hypothesis 1 tests whether there exists a significant positive relationship between users that have ‘BJP’ in their description and their likelihood of posting tweets with motivational frames. Here, we seek to understand whether assertions of partisan identity has any relationship with the user’s propensity to make demands when discussing #HinduUnderAttack. Figure 2 shows the marginal difference in log odds of tweeting motivational frames associated with different user and tweet characteristics. As is evident, users with ‘BJP’ in their description were 6.43% more likely ($p < 0.001$) to post motivational tweets compared to those without such labels in their description. This validates **Hypothesis 1**.

Next, **Hypothesis 2** claims that motivational frames are more likely to be used in tweets about Bangladesh, when compared to all other tweets. Using marginal contrasts from model 1, we found that, compared to the baseline, tweets about Bangladesh were 20.5% more likely, those about Pakistan were 6.98% less likely, and tweets about both were 8.05% more likely to have motivational frames. This finding is significant given our previous findings: namely that motivational tweets are preferred by users who identify with the BJP. When juxtaposed, these findings indicate an effort to leverage issues surrounding Bangladesh in Indian domestic politics. We discuss this aspect in more detail in the discussion section.

Finally, **hypothesis 3** tests whether motivational frames yield higher retweets from the audience. Figure 3 shows the results of the linear regression model that estimates the relationship of our covariates with retweets. Because the dependent variable is log-transformed, we convert coefficients to percentage changes using $e^\beta - 1$. Tweets that contain motivational frames are associated with approximately 7.5% more retweets than those that don’t ($\beta = 0.072, p < 0.001$). In addition, we observe Hindu-victim (+10.8%, $p < 0.001$) and Muslim-antagonist (+25.3%, $p < 0.001$) frames are significantly more likely to receive amplification through retweets. On the other hand, gender-based (-5.9%, $p < 0.001$) and thematic (-10.7%, $p < 0.001$) frames received significantly fewer retweets. Episodic tweets showed a small but significant negative association with retweeting behavior (-1.9%, $p = 0.030$).

Co-occurrence of Frames Figure 4 shows the log odds ratios for co-occurrence between all possible frame combinations. For complete results with confidence intervals and p-values of these estimates, see Table A2 in appendix. Motivational framing co-occurs significantly with all other frame types, most strongly with episodic, Hindu-victimhood and Muslim-antagonist frames. This indicates that calls to action are frequently birthed in events and refer to individuals. They are also embedded within narratives of grievance (Hindu-victim) and attribution of blame

Frame co-occurrence (log odds ratios)

Darkers cells indicate stronger co-occurrence. All estimates are significant at $p < 0.001$.

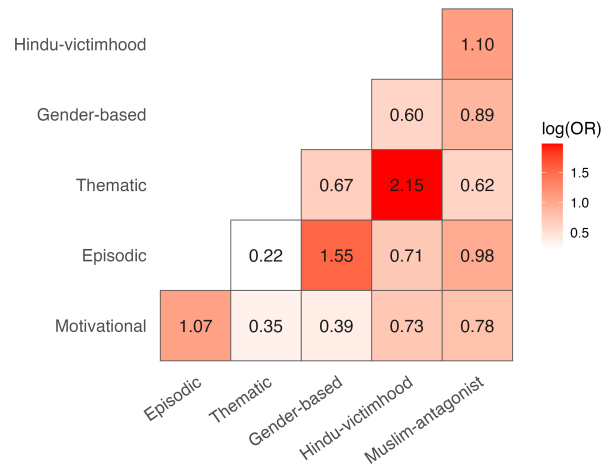


Figure 4: Heatmap of pairwise frame co-occurrence measured using log odds ratios. Values greater than zero indicate that two frames are more likely to appear together than expected by chance, with larger values corresponding to stronger co-occurrence. All estimates are significant at $p < 0.001$. Full results are included in the appendix.

(Muslim-antagonist). We also observe especially strong co-occurrence between thematic and Hindu-victimhood frames, suggesting that generalized narratives of victimization are often articulated through broader, cross-event claims rather than episodic references. These patterns illustrate that the discourse in this networked public is structured around recurring combinations of motivational appeals and issue-specific frames, rather than single, standalone framing devices.

Discussion

We center our discussion on three key facets of our findings: the use of motivational frames in different events in our study period, their use by politically affiliated users, and audience response to motivational framing. We also briefly discuss framing choices in the discourse surrounding Pakistan and Bangladesh.

Event-specific Framing

Across the five major peaks of #HinduUnderAttack, discourse centered on specific incidents and individuals. In October 2021 and April 2022, attacks on Hindus during festivals dominated, combining victimhood narratives with motivational frames. Hashtags such as #SaveBangladeshi-Hindus, #HinduLivesMatter, and #HinduWakeUp framed Hindus as victims requiring mobilization. The concurrent use of victimization and motivational framing aligns with Dunn’s findings that victimhood fosters empathy and collective grievance (Dunn 2004).

In June 2022, discourse focused on BJP spokeswoman Nupur Sharma, who was criticized for remarks on the

Prophet's alleged child marriage, and the murder of Kanhaiya Lal by two Muslim men. Sharma's suspension from the party, following protests and Middle Eastern condemnations, was framed as government capitulation to anti-Hindu forces. Victimhood frames merged with motivational (#JusticeForKanhaiyaLal) and antagonist-focused tags (#IslamicTerrorismInIndia). This blend of episodic (Kanhaiya Lal) and thematic (Islamic terrorism) framing reflects patterns found in the #MeToo movement in China, where personal narratives paired with calls for structural change (Li et al. 2021).

In August 2022, BJP lawmaker T. Raja Singh's arrest for anti-Prophet remarks provoked outrage. Frames again combined Hindu-victim and Muslim-antagonist themes with motivational tags like #ArrestOwaisi⁶. Echoing (Li et al. 2021), this illustrates strategic framing to identify victims, antagonists, and make specific demands. Hashtags such as #BJP_Fattu_Hai (BJP is cowardly) criticized the BJP itself for weakness, a pattern also seen in the Sharma controversy.

Framing and Political Identity

Past research by (Zhang et al. 2023b) and (Chebrolu et al. 2024) shows that framing choices in social movements often differ by partisan or ideological preferences of the users. We observe that users who showed some inclination or affiliation with the BJP in their Twitter bio framed tweets differently in #HindusUnderAttack digital public. Specifically, they were more likely to tweet with motivational frames. This also resonates with findings from the work of Mendelsohn et al. (Mendelsohn et al. 2024), which shows that organizational affiliation was positively associated with choice of motivational framing. This matters because users who explicitly claim affinity or affiliation with an organization (eg. the BJP) are expected to further the group's political priorities. Their greater use of motivational framing in the #HindusUnderAttack discourse raises pertinent questions about the organic nature (or lack thereof) of networked publics that perpetrate victimization narratives on behalf of dominant groups around the world. For instance, do nativist groups weaponize claims of gender-based crimes allegedly committed by migrants to build support for anti-migration policies? Does disproportionate coverage of crimes committed by minorities help perpetrate narratives that support disproportionate incarceration of those groups? Our findings necessitate researchers to explore the political economy latent in such narratives around the world.

Frame-type and Engagement

We see that motivational, Hindu-victim, and Muslim-antagonist frames invite higher audience engagement, as measured by retweets. This matches findings from prior works that show how motivational frames can capture more attention and amplification.

A key concern here is whether the choice of motivational framing reflects incentives tied to audience engagement or

⁶Owaisi is a Muslim Member of Parliament from Hyderabad, Telangana

strategic efforts by the Hindutva movement to mobilize public opinion toward their socio-political goals. Although this data set cannot fully answer this question, it is pertinent for future research in framing choices of social movements and online campaigns to consider the incentives of motivational frames vis-a-vis audience response, especially its potential for virality.

Framing on Pakistan and Bangladesh

Framing choices by users when they mention Pakistan and Bangladesh are revelatory. First, tweets about Bangladesh are significantly more likely to contain motivational frames than the baseline. We also know that motivational frames are a critical tool the online campaigns leverage to drive engagement. We aver that such framing is a strategic choice by users who identify with the BJP, given the notable online and offline incentives to connect the issue of migrants to local politics.

In the past few years, Bangladesh has become more salient to Indian domestic politics, especially with regards to unauthorized border crossings. In the bordering states of West Bengal and Assam, the BJP and its ideological affiliates in the Hindutva space have tied the issue of migration from Bangladesh to ideas of nativity and indigeneity. In both states, the emphasis on attacks on Hindu minorities in Bangladesh helps establish the dichotomy between Hindu refugees from Bangladesh and Muslim 'infiltrators' from Bangladesh (Malji and Raza 2021). This further delegitimizes Muslims as outsiders and unauthorized migrants (Malji and Raza 2021; Datta 2022; Sarma and Hazarika 2023). In Assam, this discourse has evolved into a confluence of Assamese ethno-nationalist and Hindutva ideologies (Jha and Chakrabarty 2023; Malji and Raza 2021), as both seek to paint Bengali-speaking Muslims as outsiders. On the other hand, in West Bengal, where language cannot be used as an identity marker to differentiate Hindus and Muslims, the discourse has emerged along gendered frames of 'love jihad' (Malji and Raza 2021; Amarasingham, Umar, and Desai 2022). Furthermore, partisan political violence in Bengal has been framed along Hindu-Muslim lines, with Bangladeshi migrants being blamed as the key perpetrators (Nath and Ray 2024).

Therefore, the increased salience of Bangladesh in India's domestic politics may explain the use of motivational frames in tweets about that country, given the higher resonance such tweets receive among audiences. It also helps explain the attraction of Bangladesh over Pakistan — 5.78% of tweets against 3.63% of tweets — as a subject in the #HindusUnderAttack digital space.

Implications of Our Findings

The findings of this study engage directly with, and extend, a growing body of scholarship on framing strategies in networked social movements. In particular, the observed prevalence and effectiveness of motivational frames employed by politically affiliated users resonate with established research on the strategic role of such frames in mobilizing support and shaping collective identity (Benford and Snow

2000; Xiao et al. 2022; Mendelsohn et al. 2024). Our results corroborate prior evidence that motivational rhetoric in digital spaces yields higher levels of audience engagement (Brown and Harlow 2021; Lou et al. 2024), indicating the utility of motivational framing for online campaigns. Additionally, the marked engagement patterns associated with gender-based and Muslim-antagonist frames align with findings from studies of other polarized digital movements, where emotionally charged, group-specific frames have been demonstrated to catalyze both online participation and offline activism (Zhang et al. 2023b; Miri et al. 2024).

The significance of these results extends beyond the immediate context of the #HindusUnderAttack discourse, illuminating broader mechanisms through which digital infrastructures facilitate the construction and amplification of collective grievances. The deployment of motivational frames identified here exemplifies how online actors—particularly those with partisan affiliations—can harness emotional appeals to reinforce social and political divisions, mobilize collective action, and influence public opinion. By providing empirical evidence from the Indian context, our study contributes to cross-regional understandings of how digitally-mediated framing both reflects and intensifies contemporary identity politics, anti-migrant rhetoric, ethno-nationalist mobilization, and electoral strategies within an under-examined context, country, and region.

Notably, we do not engage with the veracity of the content in this dataset. Indeed, the arguments made by actors involved in the #HindusUnderAttack discourse are rooted in the political economy of communal prejudice in the Indian subcontinent, and are often laden with half-truths and exaggerated claims (Jain, Alavi, and Sharma 2024). Rather, our study documents the broader communicative patterns politically aligned actors deploy in such campaigns. This focus complements, yet remains distinct from, literature about misinformation by foregrounding framing as a mechanism of (often deceptive) meaning-making and mobilization. In summary, these findings underscore the importance of framing choices in shaping networked political discourse, and suggest a fruitful direction for future comparative research. Such analyses can examine the interplay of motivational, narrative, and identity-based frames across divergent socio-political contexts and digital platforms.

Moving forward, we must explore how social movements intersperse claims of victimization with agendas of othering marginalized out-groups. The tactful derivation of hashtags like #HinduLivesMatter should be studied in line with past work on publics like #AllLivesMatter and #BlueLivesMatter (Goodman, Tafi, and Coyle 2022; Goodman, Perkins, and Windel 2024; Agudelo and Olbrych 2022) that connect defensive digital counterpublics with the wider socio-political environment. Furthermore, frames of victimization of women by out-groups is a common strategic tool across countries, especially in migrant-related discourse. Any analysis of networked publics like #HindusUnderAttack must consider latent political agendas driven by ideologies or partisanship.

Conclusion

In this study, we focused our attention on the use and utility of framing in the #HindusUnderAttack discourse on Twitter. We sought to answer whether online actors who showcase partisan identities use motivational frames preferentially, whether framing preferences relate to geo-political context, and if such frames receive higher amplification on Twitter/X. We also considered the socio-political underpinnings of these patterns of framing. Moreover, we considered users' choice of frame combinations (RQ2). To this end, we used finetuned BERT-based models to label the entire corpus of tweets (N=63,156) and rely on logistic regression models to confirm all three of our hypotheses.

We show that users who express a partisan affinity with the BJP - India's ruling party – are more likely to post more tweets with motivational framing compared to other users (H1). Support for H2 shows that motivational frames are more likely to be used in tweets about Bangladesh, one of India's two Muslim majority neighbors and relevant to domestic electoral politics in bordering provinces. Finally, we validate H3 to show that motivational framing relates to higher audience engagement, as measured by retweets. Furthermore, we found that users were most likely to combine motivational frames with episodic, Hindu-victim, and Muslim-antagonist frames. This is a vital finding given that motivational tweets yield higher retweets and are also preferred by supporters of the ruling party. Moreover, it suggests that the #HindusUnderAttack discourse is driven in good measure by the politics of religious polarization, migrant-native conflicts, and Islamophobic rhetoric.

Limitations

While our study extends the field significantly, several limitations persist. First, we did not analyze visual content. Brown and Harlow (2021), and Molder et al. (2022) show that visual framing generates stronger reactions on social media. Future studies should consider the multi-modal nature of framing on digital platforms. Second, our unit of analysis was an individual tweet. Framing effectiveness depends on who posts: Lou et al. (2024) show motivational frames resonate more when delivered by out-group actors, underscoring the role of messenger credibility. While we captured some attributes (e.g., partisan affiliation from user descriptions), systematic analysis of user characteristics was beyond the scope of this dataset. Third, our dataset is a random sample from Twitter's API, not a census of all #HindusUnderAttack tweets. Although we find no evidence that sampling biases frame occurrence, a complete dataset could allow richer study of user interactions. Fourth, our study cannot make causal claims about the intent behind the framing we observed. Such a study would need suitable controls, a more representative sample, and data over a longer duration. Fifth, we only explored retweets as an engagement metric. Several other behaviors such as likes, shares, comments, and quotes were not studied. A future study should consider a more sophisticated measure of engagement, as outlined by Muñoz-Expósito, Oviedo-García, and Castellanos-Verdugo (2017).

Sixth, we must consider how limitations of our dataset impact the generalizability of our classifiers, and the subsequent findings. Some frames, like thematic and Muslim-antagonist, were harder to code both in manual annotations and automated classification. This is reflected in relatively lower model performance for these frames. Moreover, the scope of our dataset is limited to tweets about specific events that occurred during the study period, and individuals connected to them. As the contours of electoral politics evolve with time, and new events shape the #HindusUnderAttack discourse, narratives and framing patterns also shift accordingly. Therefore, we must be cautious in generalizing the classifiers built in this study, and the findings that follow, to a polity or time beyond the scope of this project.

Acknowledgments

We would like to thank Dr. Weiai Wayne Xu and his team, based at the University of Massachusetts Amherst, for collecting and sharing the data we used in our analysis. This work was partially supported by the National Science Foundation (Grant IIS-1815875).

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Paper Checklist

1. For most authors...

- (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? **Yes, because our work does not profile any community, nor does it include any personal details of the social media handles we studied.**
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper’s contributions and scope? **Yes, because we have harmonized the paper’s claims across the abstract, introduction, and other sections of the paper. See also **Limitations** section on page 10 for qualifications of our claims.**
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes, we list comparable peer-reviewed research in this domain that used similar approaches.**
 - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **Yes, we clarify the potential bias in the dataset in our **Limitations** section. We also list out other limitations of our project.**
 - (e) Did you describe the limitations of your work? **Yes, please see **Limitations** on page 10**
 - (f) Did you discuss any potential negative societal impacts of your work? **Yes, See below**
 - (g) Did you discuss any potential misuse of your work?
 - (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes, we have described our data and model in detail and plan to release the anonymized Twitter data along with the paper for reproducibility.**
 - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes, and our paper conforms with them**
2. Additionally, if your study involves hypotheses testing...
 - (a) Did you clearly state the assumptions underlying all theoretical results? **Yes**
 - (b) Have you provided justifications for all theoretical results? **Yes**
 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? **Yes**
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? **Yes**
 - (e) Did you address potential biases or limitations in your theoretical framework? **Yes**
 - (f) Have you related your theoretical results to the existing literature in social science? **Yes, see **Background** section on page 2**
 - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? **Yes, see **Discussion** section**
 3. Additionally, if you are including theoretical proofs...
 - (a) Did you state the full set of assumptions of all theoretical results? **NA**
 - (b) Did you include complete proofs of all theoretical results? **NA**
 4. Additionally, if you ran machine learning experiments...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **No, but we plan to provide all the code and data with the camera-ready version**
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **Yes, see **Data & Methods** section on page 4**
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **Yes, the figures that show results of statistical modeling include confidence intervals.**
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **Yes**
 - (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? **Yes**
 - (f) Do you discuss what is “the cost“ of misclassification and fault (in)tolerance? **Yes**
 5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity...**
 - (a) If your work uses existing assets, did you cite the creators? **No, because we are using a new dataset that is not published**
 - (b) Did you mention the license of the assets? **NA**
 - (c) Did you include any new assets in the supplemental material or as a URL? **NA**
 - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? **NA**
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **NA**
 - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see FORCE11 (2020))? **No, but we plan to in the camera-ready when the data is released**
 - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see Gebru et al. (2021))? **No, but we plan to in the camera-ready when the data is released**
 6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity...**
 - (a) Did you include the full text of instructions given to participants and screenshots? **NA**

- (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? *NA*
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? *NA*
- (d) Did you discuss how data is stored, shared, and de-identified? *NA*

Appendix

The appendix includes the following information: (1) A sample of tweets, color-coded for our framing typology, (2) complete results of the contingency tables for frame co-occurrence, and (3) the typological definitions for each frame.

Sample of Tweets from the Dataset

Table A1: Examples of tweets posted with #HindusUnderAttack. Some words and phrases are color-coded if they meet the definition of each of our six frames: Episodic, Thematic, Motivational, Gender-based, Hindu-victim, Muslim-antagonist

#Attacked on #Hindu and #Hindu #iskon temple in #Bangladesh is #condemnable #govt should quick action against #culprit #Hindus_Attacked_In_Bangladesh #HindusLivesMatter #HindusUnderAttack @narendramodi @rashtrapatibhvn @albd1971 @IskconInc @UN @UNHumanRights

#Bangladeshi infiltrators are living lavishly in India. Their human rights are & national security. Whereas #BangladeshiHindusareHelpless being crushed, their rights r being trampled upon .But India accepts #Rohingyas, not #HindusUnderAttack This MUST be stopped .

#Hindu massacre continue in #Bangladesh Latest,, Save BANGLADESHI Hindus ,#SaveBangladeshiHindus #HindusUnderAttack @narendramodi @sambitswaraj @AMISHDEVGAN @UN_HRC @DChaurasia2312 @IskconInc

”Progressive” people when A hindu gets offended : You are intolerant . Its you who have to strengthen his beleifs. A muslim pelts stones : Hindus provoked him. They went to ”muslim areas”. Matlab chit bhi tumhari aur pat bhi! #HindusUnderAttack #RamNavami #khargone #Hindutva

Jhangirpuri C-Block is infested with Bangladeshi Rohingyas. They are responsible for all crimes here but nobody listens to us”. Jahangirpuri shopkeepers after the violence #HinduLivesMatter #HindusUnderAttack

#DelhiRiots #Jahangirpuri Hanuman JanMotsav Shobha Yatra attacked by Particular Miscreants #HindusUnderAttack #hinduswakeup #HinduLivesMatters

#Fact.In Bharat if Hindus are not prepared to face these extremist peaceful ass holes. Then Get ready for the genocide for Hindus by these extreme ass holes. #HindusUnite #HindusUnderAttack

#Hindus in the Nepal show solidarity for #NupurSharama #NupurSharama⁷ while her own party deserted her in time of need She said what is written in their BOOK. If peaceful get offended should contest in the court not on the streets Don` t underestimate us #HinduRashtra #HindusUnderAttack

#WestBengal had gone to dogs under @MamataOfficial rule too many Jihadis are imported from #Bangladesh to #HindusUnderAttack and spread #IslamicTerrorismInIndia need major surgery now @HMOIndia @NIA_India @PMOIndia

#ArrestOwaisi #HindusUnderAttack On July 2, 2016 Assaudin owaisi said that his party would provide legal help to the youths arrested by the NIA on charges of involvement in an alleged ISIS terror module. This is his reality.

#Hinduphobia #Hinduphobia in #US ? Man held for beating up #Indianwomen, their husbands.At least 14 #Hindu women have been targetted, but DA Rosen claims there could be more.#HindusUnderAttackInUSA #HindusUnderAttack#UnitedStates

Results of Contingency Tables for Frame Co-occurrence

Table A2: Pairwise frame co-occurrence (odds ratios)

Frame A	Frame B	OR	95% CI	<i>p</i>
Motivational	Episodic	2.92	[2.80, 3.04]	< 0.001
Motivational	Gender-based	1.47	[1.42, 1.53]	< 0.001
Motivational	Hindu-victimhood	2.07	[2.00, 2.14]	< 0.001
Motivational	Muslim-antagonist	2.19	[2.12, 2.26]	< 0.001
Motivational	Thematic	1.42	[1.37, 1.46]	< 0.001
Episodic	Gender-based	4.72	[4.40, 5.07]	< 0.001
Episodic	Hindu-victimhood	2.04	[1.96, 2.12]	< 0.001
Episodic	Muslim-antagonist	2.67	[2.57, 2.78]	< 0.001
Episodic	Thematic	1.25	[1.20, 1.29]	< 0.001
Gender-based	Hindu-victimhood	1.83	[1.75, 1.91]	< 0.001
Gender-based	Muslim-antagonist	2.43	[2.33, 2.53]	< 0.001
Gender-based	Thematic	1.95	[1.87, 2.03]	< 0.001
Hindu-victimhood	Muslim-antagonist	3.00	[2.89, 3.11]	< 0.001
Hindu-victimhood	Thematic	8.57	[8.23, 8.91]	< 0.001
Muslim-antagonist	Thematic	1.86	[1.80, 1.92]	< 0.001

Notes: Odds ratios (OR) greater than 1 indicate that the two frames co-occur more frequently than expected by chance. P-values are from contingency-table tests; all reported associations are statistically significant at $p < 0.001$.

Typological Definitions of Frames

Episodic Frames

Episodic frames reference time-bound events. They include:

- Present-day or historical events, specified by place, time, or individuals.
- Folklore or historical narratives of Hindu–Muslim conflict.
- Mentions of persons, organizations, or locations tied to events.
- Explicit temporal references (e.g., dates, years).

- Event-linked hashtags (e.g., #JusticeForXYZ), excluding #HindusUnderAttack.

Thematic Frames

Thematic frames highlight abstract or systemic issues. They include:

- Generic commentary on Hindu victimization without event-specific detail.
- References to broad entities (e.g., countries, parties) instead of individuals.
- Historical or scriptural references applied to current contexts.
- Linking multiple events to show patterns over time or geography.
- Attributing responsibility to institutions (government, media, police).
- Demands for systemic change rather than targeting individuals.
- Broad-trend hashtags (e.g., #HinduLivesMatter, #IslamicTerrorism).

Motivational Frames

Motivational frames demand or imply action. They include:

- Calls for arrests or punitive measures against alleged perpetrators.
- Implicit motivational statements (e.g., “When will you act?”).
- Boycotts of goods, services, or industries, including Bollywood.
- Justice-related demands (e.g., #JusticeForKanhaiyaLal).
- Indirect boycott endorsements (e.g., “I’ve boycotted XYZ for months”).
- Demands or rhetorical questions directed at individuals (“Do something”).
- Statements of necessity using “should,” “must,” or “needed.”
- Any action-demanding hashtag

Gender-based Frames

Gender-based frames focus on Hindu women. They include:

- References to attacks, injustice, or victimization of Hindu women/girls.
- Mentions of ‘Love Jihad’ as organized targeting of Hindu women.
- References to Nupur Sharma

Hindu-Victim Frames

Hindu-victim frames emphasize bias or violence against Hindus. They include:

- Claims of violence/discrimination against Hindus or individuals as proxies.
- Victim-focused hashtags (#JusticeForShraddha, but not #ShraddhaWalkar).

- Events framed as targeting Hindus (e.g., #lovejihad).
- Allegations of anti-Hindu bias by individuals or institutions.
- Criticism of Hindu festivals or practices.
- References to insults against Hindu traditions or deities.
- Note: #HinduRashtra is not Hindu-victim framing.

Muslim-Antagonist Frames

Muslim-antagonist frames depict Muslims/Islam negatively. They include:

- Negative adjectives explicitly tied to Muslims or Islam.
- Allegations of Muslim-perpetrated violence or disorder.
- Use of stereotypical names, phrases (“peaceful community”), or terms like “Urduwood,” “Sar Tan Se Juda.”
- Mentions of Bangladesh or Pakistan with antagonistic framing.
- Dog whistles against minorities (#conversionmafia).
- Urdu terms with negative attributes (e.g., “nafrati Owaisi”).
- Calls for action against Muslim individuals (#arrestowaisi).
- Claims of Muslim favoritism by institutions (media, judiciary).
- References to controversial films (e.g., *The Kashmir Files*).