

Framing Unionization on Facebook: Communication Around Representation Elections in the United States

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Abstract

Digital media have become central to how labor unions communicate, organize, and sustain collective action. Yet little is known about how unions' online discourse relates to concrete outcomes such as representation elections. This study addresses the gap by combining National Labor Relations Board (NLRB) election data with 158k Facebook posts published by U.S. labor unions between 2015 and 2024. We focused on five discourse frames widely recognized in labor and social movement communication research: diagnostic (identifying problems), prognostic (proposing solutions), motivational (mobilizing action), community (emphasizing solidarity), and engagement (promoting social media interaction). Using a fine-tuned RoBERTa classifier, we systematically annotated unions' posts and analyzed patterns of frame usage around election events. Our findings showed that diagnostic and community frames dominated union communication overall, but that frame usage varied substantially across organizations. Greater use of diagnostic, prognostic, and community frames prior to an election was associated with higher odds of a successful outcome. After elections, framing patterns diverged depending on results: after wins, the use of prognostic and motivational frames decreased, whereas after losses, the use of prognostic and engagement frames increased. By examining variation in message-level framing, the study highlights how communication strategies correlate with organizational success, contributing open tools and data, and complementing prior research in understanding digital communication of unions and social movements.

Introduction

Digital media has transformed the landscape of collective action. Civil Society Organizations (CSOs), interest groups, and social movements increasingly rely on online platforms to mobilize participants, coordinate activities, and frame issues to reach broader audiences. Scholars have highlighted the promises of these digital technologies: lowering barriers to participation, enabling new forms of connective action, and amplifying marginalized voices. At the same time, they have cautioned about their limitations, including resource constraints, fragmented attention, and uncertain effects on long-term organizational capacity (Bennett and Segerberg 2012; Earl and Kimport 2011; Tufekci 2017).

Labor unions provide a distinctive case within this ecosystem. As one of the most institutionalized forms of collective organization, they have experienced declining membership and political influence in the United States since the mid-twentieth century. This led scholars to ask whether their revitalization requires not only traditional collective bargaining but also new forms of communication and public engagement (Milkman 2013; Hurd 1998; Voss and Sherman 2000). Given today's fragmented workforce with precarious employment and immigrant labor (Milkman 2020), social media platforms offer a strategic opening for unions. Accordingly, unions have adopted digital media as a communication infrastructure to mobilize members, reach new audience, and maintain organizational relevance (Lee 1996).

Among digital platforms, Facebook has emerged as particularly important (Carneiro and Costa 2022; Ford and Sinpeng 2022). Like other social media, it supports both outward and inward communication, and attracts users whose demographic profiles resemble many unionized workforces. These features make it strategically relevant for labor mobilization (Blanc 2022). In this study, we focus on Facebook for both substantive and practical reasons. Among the 77 unions affiliated with the AFL-CIO¹ (the largest federation of unions in the United States), 63 link to Facebook, 66 to Twitter, and 43 to YouTube. Although Twitter is slightly more prevalent, its data has become increasingly restricted (Murtefeldt et al. 2024). Facebook therefore offers both broad adoption and comparatively accessible data, making it well suited for empirical analysis. Despite its potential, much remains unknown about how unions use the platform effectively: there is uncertainty about which engagement strategies are most effective (Greene and Kirton 2003), and about how union communication on the platform relates to concrete unionization outcomes at scale.

In this study, we combined National Labor Relations Board (NLRB) election data with a large corpus of Facebook posts by labor unions in the United States from 2015 to 2024 to examine the correlation between online communication and representation election outcomes. Representation elections are administered by the NLRB and allow eligible employees to vote on whether a union should be certi-

fied as their exclusive bargaining representative. Such elections occur regularly across industries, initiated by employee petitions. Using natural language processing and computational methods, we analyzed how unions framed their digital communication around representation elections and whether these patterns varied by electoral outcomes². Specifically, we addressed three research questions:

RQ1. *To what extent do labor unions use discourse frames in their Facebook communication?*

RQ2. *How is the use of different discourse frames prior to an election associated with the likelihood of electoral success?*

RQ3. *How do patterns of frame usage change after election events, and do these dynamics vary between wins and losses?*

While our primary analysis focused on discourse frames, prior research on communication suggests that the emotional content can shape mobilization (Feldman and Hart 2016) and that the topics discussed may influence audience response (Wang and Zhou 2021). We therefore complemented our frame-based analysis with emotion detection and topic modeling to provide a more nuanced view of union communication.

Our contributions are threefold: (i) we provide guidelines for annotating discourse frames in unions' social media text, (ii) we release a fine-tuned, ready-to-use classification model for detecting frames in unions' communication; and (iii) we advance research at the intersection of framing and labor movement, offering insights into the relationship between digital communication and unionization dynamics. Although much of labor movement scholarship treats unions at the collective level (Snow, Benford et al. 1988; Benford and Snow 2000; Kelly 1998; Voss and Sherman 2000), we show how digital data enables the observation of framing strategies at the level of individual messages and connect them to concrete organizational outcomes. This micro-comparative approach fits well with the heterogeneity of communication practices across unions, and allows us to study how framing varies during periods of organizational change.

Building on this perspective, our analysis of union communication on Facebook revealed several key patterns. We found that unions predominantly emphasized problem identification and community-building, though frame use varied across organizations. The mobilization potential, embodied by a discourse centered on call-to-action messages, remained largely untapped. This pattern echoes prior research showing that unions and CSOs tend to prioritize problem framing and information dissemination on social media, while making more limited use of call-to-action messages (Lovejoy and Saxton 2012; Uba and Jansson 2021; Carneiro and Costa 2022). Unions representing broad, multi-industry workforces (*industrial* unions) tended to emphasize frames for grievances and solutions, whereas unions representing specialized trades (*craft* unions) relied less on these frames. By fitting a Bayesian logistic regression model

to predict representation election outcomes, we found that a greater focus on problem identification, solution-oriented messaging, and community building prior to the election is associated with higher odds of winning. In cases that were won, solution-oriented and call-to-action frames generally declined after the election. In cases that were lost, by contrast, solution-oriented and interaction-focused frames increased after the election. Overall, these results indicate that election outcomes are associated with distinct patterns of communicative emphasis. These results are based on observational data and do not allow us to make causal claims about the effect of frames on electoral success. The association between communication strategies and organizational outcomes, as well as their adjustment after victory, is also reflected in prior work on union revitalization (Turner 2005) and theories of organizational life cycles of social movements (Christiansen 2009; Tarrow 2022).

Our findings provide actionable insights for labor unions, CSOs, interest groups, and social movements on their digital communication strategies. In particular, successful election outcomes are more frequently associated with social media use emphasizing issue discussion, the proposal of solutions, and solidarity rather than engagement prompts (e.g., encouraging likes or shares) or mobilization cues. Beyond these practical implications, our results contribute to theoretical debates on framing and collective action by showing how message-level strategies vary across organizations and electoral contexts. By shifting focus from collective-level analyses of movements to the micro-dynamics of discourse on digital platforms, this study offers a lens for examining how framing may be involved in processes of adaptation during periods of organizational change.

Theoretical Framework: Discourse Frames

Labor unions, like other CSOs, interest groups, and social movements, rely on communication to achieve core organizational goals and lobbying. Nowadays, much of this activity occurs in digital spaces, making it critical to understand the communicative strategies unions employ online.

Framing is central to communication studies, but its meaning varies across traditions. In rhetorical approaches, frames selectively emphasize certain considerations to shape audience interpretations (Gamson and Modigliani 1989; Tversky and Kahneman 1981; Druckman 2001; Kinder 1998). Social movement research treats frames more broadly as recurring points of emphasis that structure problems, propose solutions, and motivate action (Snow, Benford et al. 1988; Benford and Snow 2000), highlighting meaning-making and collective behavior rather than persuasion. Interest group research similarly sees framing as strategic and instrumental (Baumgartner et al. 2009), but emphasizes deployment under specific political or organizational conditions rather than exhaustive typologies. Building on these perspectives, we adopt a functional view of frames in union social media, analyzing a selective subset that reflects their role in organizing meaning and facilitating collective action. Although not exhaustive, these categories provide a theoretically grounded and analytically appropriate framework for studying labor union communication online.

²Data and code are available at <https://github.com/ariannap13/laborunions>

The theory of collective action frames (Snow, Benford et al. 1988; Benford and Snow 2000) offers a central lens for analyzing frames and functions of unions' social media communication: **diagnostic** frames, which highlight problems and assign responsibility; **prognostic** frames, which propose solutions; and **motivational** frames, which seek to mobilize audiences. These three core frames also parallel the conditions for union revitalization outlined by Kelly (1998): workers must recognize grievances (diagnostic), perceive them as actionable (prognostic), and see unions as legitimate vehicles for change (motivational).

To capture the specificity of union communication online, we draw on literature on organizational and movement communication on social media (e.g., Lovejoy and Saxton 2012; Carneiro and Costa 2022; Muntinga, Moorman, and Smit 2011), which identifies a comprehensive range of frame types. Guided by iterative analysis of the data, we focus on those categories that are both theoretically meaningful and empirically prevalent. Specifically, we examine two frame types. **Community** frames emphasize shared identity and solidarity without urging action (Carneiro and Costa 2022; Lovejoy and Saxton 2012), while **engagement** frames promote platform-specific interaction (e.g., liking, sharing), reflecting the affordances of social media (Muntinga, Moorman, and Smit 2011).

In summary, our analysis operationalized five discourse frames:

- **Diagnostic:** identifying problems and attributing responsibility.
- **Prognostic:** advancing solutions and strategies for change.
- **Motivational:** encouraging participation through calls to action relevant to union goals (e.g., urging followers to join a union or attend protests).
- **Community:** fostering solidarity and collective identity, without prompting a specific action.
- **Engagement:** leveraging social media affordances (likes, shares, comments) to sustain visibility and algorithmic reach, rather than to mobilize action or express collective identity.

This framework maps prior research on framing and union communication onto an operationalization of key framing functions observable in social media discourse.

Methodological Framework

Data Curation

Our focus is on the central stage of the unionization process: representation elections and their outcomes (win or loss). We collected data on election results from publicly available records of the NLRB (National Labor Relations Board 2025), covering all cases for which a representation election (RC cases in the NLRB data) was petitioned and held between January 2015 and December 2024 for labor unions in the United States. From the available variables, we focused on the numeric identifier of each election case, the election date, the names of participating unions, and the union that won the election.

The dataset comprises 11,416 election cases, of which 10,975 involve a single union, 417 involve two unions, and 24 involve three unions competing in the same election. On average, there were 20 elections per week between 2015 and 2024. Once elected, a union remained the representative for a given set of workers for an average of 237 days. Since much of the information was entered manually in the NLRB data, union names exhibit considerable variation in formatting and granularity. To facilitate analysis of unions' Facebook (FB) activity, we standardized these names at the national or international level. For example, "Communications Workers of America Local 7250" was mapped to "Communications Workers of America." To identify a set of national and international unions, we began with the official list of unions affiliated with the AFL-CIO, consolidating subunits under their parent organizations (e.g., *TNG-CWA* under *CWA*) using regular expressions and rule-based assignments. This process yielded 47 unions. For unions not included in the AFL-CIO list, we identified common patterns and acronyms using a combination of regular expressions (e.g., extracting acronyms in parentheses) and manual grouping. This resulted in additional 510 potential national and international unions, including a substantial amount of noise from local chapters which we could not easily reconduct to parent unions.

To link these organizations with their digital presence, we queried the Bing Search API³ with each union name alongside the string "union Facebook" to identify official FB pages. We parsed the results using regular expressions and manually verified their accuracy. This resulted in 66 unions with official FB pages, of which 40 provided downloadable data through the Meta Research API Content Library (Meta Platforms, Inc. 2024)⁴. While the resulting number of unions included in the dataset may appear limited, these unions collectively represent approximately 46% of all union members in the United States in the 2024 fiscal year⁵. Table E1 lists the unions involved in the study, along with their acronyms and type of structure. In total, we collected 158,238 posts (157,883 of which had text available) published between January 2015 and December 2024, matching the time span of the election data.

Of the 11,416 NLRB election cases, we identified 2,607 instances where unions with available FB data lost and 6,445 where they won.

Control Factors We collected data on union characteristics and social media activity to account for factors that may influence election outcomes.

Traditional union-level variables were drawn from public records published by the U.S. Department of Labor⁶ and by the Center for Union facts⁷. These include the number

³Microsoft Bing Search API. <https://api.bing.microsoft.com/v7.0/search>. Accessed March 3, 2025

⁴According to the API terms, data are only downloadable for pages with at least 15,000 followers or likes.

⁵Data from <https://www.dol.gov/agencies/olms/public-disclosure-room>

⁶<https://www.dol.gov/agencies/olms/public-disclosure-room>

⁷<https://unionfacts.com/find-your-union/>

of members, assets, disbursements, liabilities, and primary industry (e.g., construction, educational services). From the NLRB election data, we recorded the state in which each election occurred to capture broader state-level institutional and political context. Separately, we coded whether the election took place in a *right-to-work* jurisdiction, capturing a specific legal dimension of state labor regimes. Finally, following a common distinction in labor movement scholarship (Herrigel 1993; Dubofsky 2000), we annotated unions for their organizational type (craft vs. industrial) through manual review of their official websites.

For social media activity, we drew on the collected Facebook data, recording follower counts and the total number of posts over the analyzed period. From the latter, we computed the average number of posts per week. To reduce multicollinearity, we evaluated Variance Inflation Factors (VIFs) and excluded variables with $VIF \geq 5$, resulting in the removal of union employees and Facebook followers from the final set of controls.

Discourse Frames Classifier

We trained a classifier to detect five discourse frames in union Facebook posts: *diagnostic*, *prognostic*, *motivational*, *community*, and *engagement*. Aiming at capturing the nuanced usage of such frames in online communication, we set the task to be multi-label. Following common practices in Natural Language Processing (NLP), we first fine-tuned a RoBERTa-base model (Liu et al. 2019) on the text of the 157,883 posts to better capture typical linguistic patterns of labor union communication on Facebook. After collecting annotations for the presence of discourse frames⁸, we further fine-tuned this model to perform the multi-label classification task. We also included a RoBERTa-base model directly fine-tuned on the frame detection task, and a BERT-base model as additional classifiers for comparison. Details on model configuration and computational resources are provided in Appendix B.

Frames Annotation We conducted a manual annotation campaign with two of the authors as coders, considering a multi-label setting for the presence of discourse frames. Starting with an initial set of 100 posts and taking inspiration from prior work on measuring collective action frames in text (Fernández-Zubieta et al. 2023; Mendelsohn et al. 2024), we iteratively defined a codebook for the identification of discourse frames of interest. The codebook is reported in Appendix A.

Using this codebook, the coders annotated a new, random sample of 200 posts, achieving a Cohen’s κ inter-annotator agreement of 0.81 averaged across labels⁹. Given this level of agreement, the coders then independently annotated disjoint sets of additional randomly sampled posts. In total, this resulted in 1,151 new posts, each annotated by a single coder. The annotated data is temporally well distributed:

⁸We also annotated posts for an additional *political endorsement* label to capture explicit support for political actors. Given its low prevalence, it was not included in the main analysis.

⁹Per-label agreement: 0.88 (diagnostic), 0.86 (prognostic), 0.86 (motivational), 0.62 (community), and 0.85 (engagement)

posts from 2016 to 2024 each account for between 5% and 14% of the sample, while 2015 contributes just over 2%.

Multi-label Classification We randomly split the annotated dataset into training (80%) and test (20%) sets. The RoBERTa model, pre-adapted to Facebook language, was then fine-tuned on the training set for the multi-label classification task. After evaluating its performance on the test set, we applied the final classifier to the entire corpus to generate frame predictions for all posts.

Supplementary Linguistic Measures

In addition to coding frames, we also computed two supplementary linguistic measures to characterize posts in more detail. First, we generated an **emotional profile** for each post based on Ekman’s six basic emotions (Ekman 1992) plus a neutral category, using a pre-trained DistilRoBERTa classifier¹⁰ to produce a probability vector over the seven emotional categories. Second, we applied **topic modeling** to posts using BERTopic (Grootendorst 2022) with DistilRoBERTa embeddings (Sanh et al. 2019).

Patterns of Frames Usage

We examined how unions’ usage of discourse frames prior to elections can contribute to the prediction of elections’ outcomes, and how frame usage changed after the elections.

To account for sparsity in posting frequency, we aggregated daily frame usage over short, overlapping windows of $n_{days} = 5$. Given an active union on Facebook, for each day and each frame, we calculated (i) the number of posts containing that frame and (ii) the proportion of such posts relative to all posts on that day. To focus on activity around elections, for each election case, we defined two non-overlapping aggregated measures:

- **pre** _{f_i} : mean proportion of posts expressing frame f from 7 to 3 days before election i .
- **post** _{f_i} : mean proportion of posts expressing frame f from 3 to 7 days after election i .

These aggregated measures exclude the election day itself—avoiding overlap caused by the moving aggregation—while capturing both the immediate lead-up and aftermath. The aggregation does not introduce temporal smoothing, as analyses rely on fixed pre- and post-election summaries.

Predicting Election Outcome To examine whether the use of specific frames was associated with electoral success, we fitted a Bayesian logistic regression model to predict the electoral outcome (win vs. loss). In this framework, regression coefficients are estimated as posterior distributions, providing a full distribution of plausible values for each effect. Weakly informative priors were automatically assigned to all coefficients using the `bambi` Python package. The model

¹⁰j-hartmann/emotion-english-distilroberta-base on Hugging-Face

was specified as follows:

$$\begin{aligned} \text{logit}(\Pr(\text{election_win}_i = 1)) &= \beta_0 + \sum_{f \in F} \beta_f \text{pre}_{fi} \\ &+ \sum_{e \in E} \beta_e \text{emo}_{ei} + \sum_{c \in C} \beta_c X_{ci} + u_{\text{union}[i]} + u_{\text{election-state}[i]} \end{aligned}$$

where election_win_i is the binary indicator of the outcome for election i , and β_0 is the intercept. Predictors fall into four groups: framing variables, other linguistic characteristics, traditional union-level controls, and online presence controls.

Framing variables are captured by pre_{fi} , the proportion of posts prior to election i using frame f (diagnostic, prognostic, motivational, community, or engagement), with coefficients β_f . Other linguistic characteristics are represented by emo_{ei} , the mean predicted probability that posts prior to election i expressed emotion e (anger, disgust, fear, joy, sadness, surprise, or neutral), with coefficients β_e . We do not include topic-level predictors in this analysis because most topics are union-specific (see Results).

Control variables X_{ci} with coefficients β_c include traditional union-level characteristics and online presence measures. These divided into traditional union level controls and online presence controls. Union-level controls comprise union size, assets, disbursements, liabilities, primary industry, organizational structure (craft vs. industrial), and the presence of a right-to-work law in the election state. Online presence is measured by the average number of weekly posts. All numerical controls are standardized. We also included normally distributed random intercepts for unions, $u_{\text{union}[i]} \sim \mathcal{N}(0, \sigma_u^2)$, and election states, $u_{\text{election-state}[i]} \sim \mathcal{N}(0, \sigma_u^2)$, to account for unobserved heterogeneity.

Detrended Frame Usage: Changes Pre- vs. Post-Election

To examine how unions adjusted their communication around elections, we computed detrended frame usage to remove long-term trends. For each union, baseline periods of 18 consecutive days were identified during January 2015–December 2024 when the union was not involved in a specific election. A pseudo-event date was assigned at the midpoint of each baseline period, and pre- and post-event aggregation was applied like for real elections.

We then computed the detrended usage of frame f as

$$\begin{aligned} \text{pre}_{fi}^D &= \text{pre}_{fi} - \text{pre}_{fi}^{\text{baseline}} \\ \text{post}_{fi}^D &= \text{post}_{fi} - \text{post}_{fi}^{\text{baseline}} \end{aligned}$$

where pre_{fi} and post_{fi} denote usage of frame f before and after the election i , and $\text{pre}_{fi}^{\text{baseline}}$ and $\text{post}_{fi}^{\text{baseline}}$ are the corresponding baseline values. Values of pre_{fi}^D or post_{fi}^D close to 0 indicate frame usage similar to baseline periods, positive values indicate higher-than-baseline usage, and negative values indicate lower-than-baseline usage.

The change from pre- to post-election was computed as

$$O = \text{pre}_{fi}^D - \text{post}_{fi}^D$$

Union-case instances were classified as **decrease**, **stable**, or **increase** using the 25th and 75th percentiles of the O dis-

tribution:

$$O = \begin{cases} \text{decrease,} & O \leq \text{percentile}_{25} \\ \text{stable,} & \text{percentile}_{25} < O \leq \text{percentile}_{75} \\ \text{increase,} & O > \text{percentile}_{75} \end{cases}$$

This procedure provided a consistent way to categorize changes in frame usage, enabling systematic comparisons between won and lost election cases and across frames.

Robustness Checks To ensure that results generalize well beyond specific design choices, we conducted several robustness checks: (i) we varied the moving aggregation window size ($n_{\text{days}} = 5$ vs $n_{\text{days}} = 3$) (see Appendix D.3); (ii) we balanced the number of won and lost cases within each labor union, repeating analyses across multiple random seeds (see Appendix D.4); and (iii) we down-sampled representation elections from unions with exceptionally high electoral activity, capping the number of cases per union at the 90th percentile of the distribution, to reduce the influence of a small number of highly active unions. Analyses were repeated across multiple random seeds (see Appendix D.4).

Results

Classification of Discourse Frames

We applied our fine-tuned RoBERTa model to Facebook posts to perform multi-label classification of discourse frames. Table 1 reports performance in terms of precision, recall, and F1 scores for the test set. Scores are comparable to similar studies (Fernández-Zubieta et al. 2023; Mendelsohn et al. 2024), with F1 values ranging from 0.68 to 0.78 across frames and a macro F1 of 0.73. To evaluate the performance of this model, we compared it against two alternative classifiers, and found that it performs on par with or better than both (see Appendix D.1).

Frame	Precision	Recall	F1-score	Support
Diagnostic	0.72	0.85	0.78	84
Prognostic	0.67	0.69	0.68	58
Motivational	0.57	0.83	0.68	29
Community	0.75	0.81	0.78	81
Engagement	0.71	0.78	0.75	51
Micro avg	0.70	0.80	0.74	303
Macro avg	0.68	0.79	0.73	303
Weighted avg	0.70	0.80	0.74	303

Table 1: Performance of the multi-label discourse frames classifier. **Support** indicates the number of examples in each class or overall.

We then applied the classifier to the corpus of 157,883 textual posts, identifying 140,199 as expressing at least one of the frames of interest.

Usage of Discourse Frames

Aiming at defining a baseline distribution of frame usage across unions, we first looked at the distributions of posts by

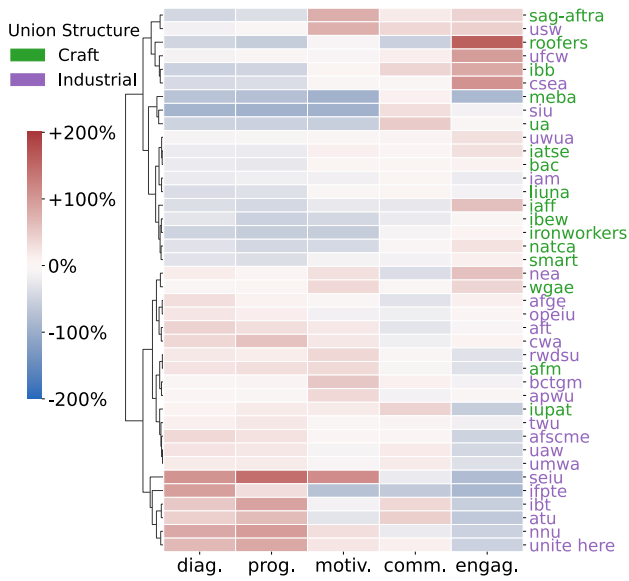


Figure 1: Relative usage of discourse frames by labor unions (percentage difference from baseline). Red indicates above-baseline usage, blue below. The dendrogram clusters unions by framing patterns across the five frames, and acronyms are colored by organizational structure.

union. We identified skewness (minimum = 779, 25th percentile = 1,921, 75th percentile = 5,442, maximum = 10,452, full distribution in Figure E1) and thus implemented a bootstrap-like down-sampling procedure. Over-represented unions were down-sampled to the minimum number of posts in the distribution, and the procedure was repeated with five different random seeds. For each frame, we computed the median proportion of posts expressing that frame across seeds. Overall, the median baseline distribution of frame usage is as follows: diagnostic in 40.7% of posts, community in 39.4%, prognostic in 28.3%, engagement in 23.2%, and motivational in 15.4%.

Figure 1 shows how individual unions diverge from the overall median baseline in their use of different frames. For each union, we calculated the share of posts expressing a given frame relative to its total output, and then expressed this value as a percentage difference over the median baseline. A value of +100% indicates that the union used that frame twice as often as the median baseline, 0% indicates equal usage, and -50% indicates that the union used the frame half as often. Many unions behaved in line with the baseline; nonetheless, a clear divide emerged. Unions clustered into two broad groups based on whether their use of diagnostic and prognostic frames was higher or lower than the baseline. In particular, industrial unions tended to employ diagnostic and prognostic frames more frequently than the baseline. Examples include the Service Employees International Union (SEIU), the International Federation of Professional and Technical Engineers (IFPTE), the International Brotherhood of Teamsters (IBT), the Amalgamated Transit Union (ATU), National Nurses United (NNU), and

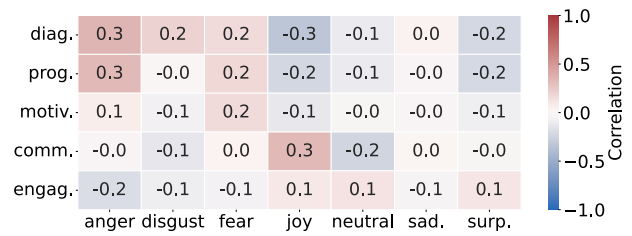


Figure 2: Pearson's correlation between frames and emotions in Facebook posts. Positive values (red) indicate positive correlations; negative values (blue) indicate negative correlations.

Unite Here (UNITE HERE), all located toward the bottom of the dendrogram (union acronyms are expanded in Table E1). By contrast, lower-than-baseline usage of diagnostic and prognostic frames was more characteristic of craft unions. This distinction might reflect different organizational orientations: industrial unions, with their broad membership bases, are more often engaged in large-scale mobilization and bargaining arenas, where diagnostic frames (grievance articulation) and prognostic frames (solution proposals) play a central role (Voss and Sherman 2000). Variation also emerged in the use of the engagement frame. Industrial unions, in particular, often used engagement frames less than the baseline (cf. bottom of the plot), whereas higher-than-baseline engagement showed no consistent relationship to union structure (cf. top of the plot). Notably, the United Union of Roofers, Waterproofers and Allied Workers (*Roofers*) employed the engagement frame nearly two and a half times more often than the baseline.

Taken together, these results suggest that industrial unions tend to differentiate themselves from craft unions by emphasizing grievance and solution-oriented frames while downplaying interactive engagement, consistent with their larger-scale bargaining and mobilization needs. Craft unions, on the other hand, appear less reliant on diagnostic and prognostic repertoires, and in some cases lean more heavily on engagement, indicating a different balance in communication strategies.

Emotional Tone To explore the affective nuance of frames, we computed correlations between frames and the emotional profiles of posts (cf. Figure 2).

Diagnostic and prognostic frames were associated with stronger negative emotions, particularly anger and fear, while community frames were moderately correlated with joy. Motivational and engagement frames showed little association with emotions. Overall, correlations were modest, suggesting that emotions provide complementary context rather than replace frames as the primary lens for interpreting union communication strategies.

Topics Discussed We also explored the thematic content of posts using topic modeling. Applying BERTopic to the full dataset yielded 308 topics with at least 50 posts each. Table 2 reports the ten most prevalent topics (excluding noise).

Topic	% documents
Education and experience of teachers	3.81
Unions as communities	2.86
Updates and news from unions	2.47
Nurses and their importance	2.04
Congratulations to union members	1.95
Teamsters events	1.31
US postal service campaigns	1.27
Promotion of apprenticeships	1.03
Promotion of voting during US elections	0.99
SAG-AFTRA events	0.96

Table 2: Topic proportions for selected topics, considering all Facebook posts.

Some topics, such as *unions as communities* and *promotion of apprenticeships*, are relatively broad and span multiple unions. Others, like *education and experience of teachers* or *nurses and their importance*, are highly union-specific. At the union level, many topics remain highly specific (see Appendix C). These observations indicate that while topic modeling captures meaningful distinctions, prominent themes often reflect the particular context of individual unions. As a result, topic modeling is more useful for qualitative insight than for generalizable inference, and is therefore not included in the predictive model.

Frames Usage Leading to Elections

We examined the use of frames in the lead-up to elections and their association with election outcomes using Bayesian logistic regression. To ensure balance, we down-sampled wins and losses within each union and fit the model across ten random seeds. To reduce collinearity, diagnostic and prognostic frame proportions were combined into a single category, as their Variance Inflation Factor (VIF) exceeded 5 when coded separately. Figure 3 presents posterior mean log-odds estimates for covariates whose posterior distributions excluded zero in at least six out of ten seeds.

Results are generally consistent across alternative modeling choices, including separate coding of diagnostic and prognostic frames, a different moving aggregation window size, and downsampling of over-represented unions (Figures D1, D2, D3, and D4).

Greater use of diagnostic/prognostic and community frames prior to elections is associated with higher odds of winning, whereas motivational and engagement frames show no consistent association with the outcome. This pattern suggests that successful campaigns tend to emphasize problem definition, solution-oriented messaging, and collective identity rather than mobilization or engagement cues.

With respect to emotional content, neutral language is positively associated with winning, while disgust-related content is negatively associated; however, these effects are less stable across robustness checks than framing effects.

State-level random intercepts indicate heterogeneity in baseline odds of winning. Posterior means for Colorado, Idaho, and Ohio are shifted toward lower baseline odds rel-

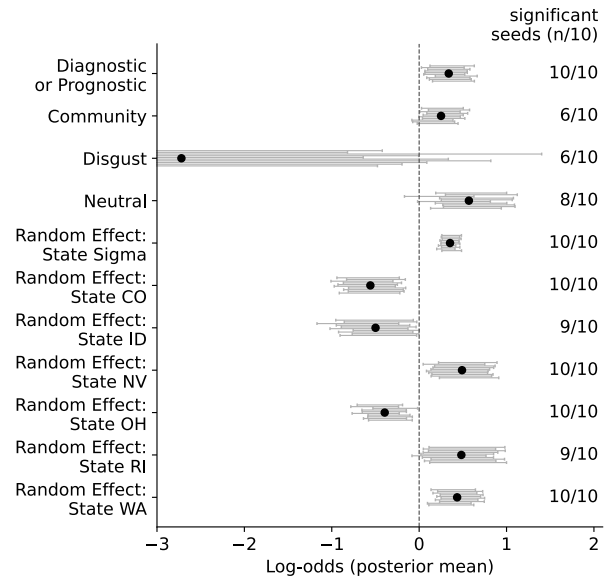


Figure 3: Posterior mean log-odds for selected variables, averaged over ten seeds. Black dots: means; grey lines: 90% HDIs per seed. Ratios: number of seeds with HDIs excluding zero (shown if ≥ 6 seeds).

ative to the global intercept, while Nevada, Rhode Island, and Washington exhibit higher baseline odds. The heterogeneity in state-level baseline odds may reflect differences in union density and organizing climate, with states such as Washington and Rhode Island exhibiting stronger labor infrastructures, while lower-density states may pose higher structural barriers to union success.

Frames Usage Pre- and Post-Elections

We finally examined how frame usage changes from the pre- to the post-election period. We first verified that frame usage before and after elections was robust to the choice of aggregation window size (see Appendix D.3). For each frame, we classified changes from pre- to post-election into three patterns: decrease, stable, or increase, depending on whether post-election usage was lower, similar, or higher than pre-election usage. We then counted the number of union-case instances with won or lost outcomes assigned to each pattern, providing an overall measure of how prevalent each change pattern was for each frame. We down-sampled the number of wins and losses per union to ensure a balanced sample. Results are robust to the choice of sampling seed, as shown in Figure D5. Figure 4 shows the difference in pattern prevalence between losses and wins, computed as *losing* minus *winning*. Positive values indicate a pattern was more common among losses, negative values indicate it was more common among wins. For example, a value of -5% in the decrease pattern for the *prognostic* frame means that in won cases, frame usage declined 5% more often than in lost cases. We computed Newcombe’s confidence intervals at $\alpha = 0.05$ for the difference between the two independent proportions and considered a difference significant if the in-

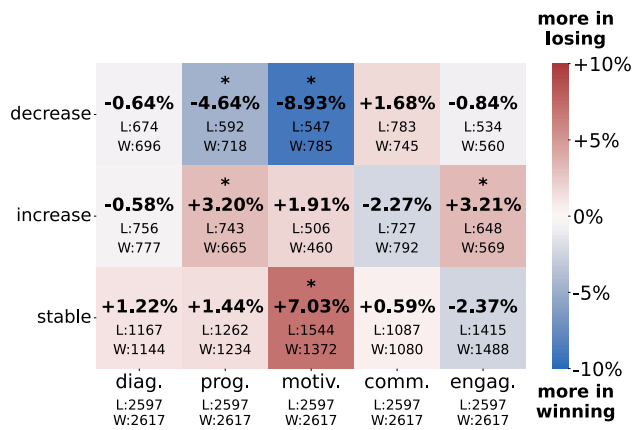


Figure 4: Changes in frame usage pre- vs. post-election, by lost and won cases. Bold values: difference in frame proportions between losses and wins. Counts: union-case instances (L=loss, W=win). *: significant difference ($p < 0.05$).

terval excluded 0.

In won cases, frame usage more often decreased for *prognostic* and *motivational* frames after elections. In lost cases, by contrast, *prognostic* and *engagement* usage increased more often, while *motivational* usage remained stable.

Robustness checks across multiple random seeds and down-sampling of over-represented unions confirmed that the decreases in *prognostic* and *motivational* frames in won cases were consistent. Other patterns were not consistently significant (see Appendix D.4).

Discussion and Conclusion

Traditional sociological research at the intersection of framing and labor movement has often taken a macroscopic perspective when investigating how movement communication relates to organizational outcomes. Such approaches typically conceptualize the labor movement at a collective level. Yet, in the age of connective action (Bennett and Segerberg 2012), political action is increasingly dispersed and decentralized (Kavada 2016), calling for more microscopic perspectives. Within social media contexts, this relates to analyzing how individual messages employ discourse frames and connecting these patterns to concrete organizational outcomes, such as labor unions' representation elections.

Some qualitative and mixed-methods studies have already demonstrated the value of this kind of granular analysis (Pasquier and Wood 2018; Frangi, Zhang, and Hebdon 2020; Lazar, Ribak, and Davidson 2020). However, these works tend to be limited to single campaigns, making generalization difficult. Quantitative analyses of union communication, in turn, often examine only a restricted number of accounts, or remain disconnected from organizational outcomes (Hodder and Houghton 2020; Houghton and Hodder 2021; Uba and Jansson 2021; Carneiro and Costa 2022). Our study addressed these gaps by contributing a micro-level, comparative analysis of 158k Facebook posts by 40 U.S. labor unions between 2015 and 2024. Building on

framing theory applied in labor and social movement research (Kelly 1998; Benford and Snow 2000; Lovejoy and Saxton 2012; Carneiro and Costa 2022), we developed an annotation codebook and a machine learning model to infer the usage of discourse frames, linking them to representation election outcomes. This approach enabled the kind of systematic, comparative work often missing in framing and social movements scholarship (Tarrow 1996; Benford 1997; Snow et al. 2014).

Prior work has documented the untapped mobilization potential of social media for unions and non-profit organizations. Their communication focus is mainly on routine activities, information campaigns, and community-building messages, with very little attention to action-focused messages (Lovejoy and Saxton 2012; Uba and Jansson 2021; Carneiro and Costa 2022). These studies also highlight the diversity of communication strategies employed across organizations. Our findings confirmed and extended these insights.

First, we found that nearly 89% of posts contain at least one frame, with diagnostic and community frames dominating overall discourse (**RQ1**). This suggests that unions rely heavily on problem identification and community-building to structure their communication. Such practices resonate with the expression of stances on problematic issues, which relate to the diagnostic frame, and celebrations of achievements, common in the community frame, stressed in Carneiro and Costa (2022). Moreover, they are close to the relationship-fostering role of social media messaging identified by Lovejoy and Saxton (2012), captured by community frames in our work. In line with such previous work, we found that the use of action-infused social media messages (i.e., our *motivational* frame) was generally very low. At the same time, substantial heterogeneity emerged across unions, again in line with previous research on diverse communication repertoires. Importantly, we observed systematic differences by organizational structure: industrial unions—organizing across skill boundaries—tended to use diagnostic and prognostic frames more than the baseline, whereas craft unions—organized around specialized skill sets—used them less. This pattern resonates with their distinct organizational orientations, with industrial unions more often engaged in large-scale mobilization and bargaining.

Second, we found that a higher usage of diagnostic, prognostic, and community frames in Facebook communication prior to elections was associated with higher odds of winning (**RQ2**). This finding matches the literature on innovative strategies and union revitalization (Turner 2005), suggesting that successful unions may engage in versatile and intensive framing strategies. It also aligns with research linking frames of injustice and solidarity to mobilization outcomes (Benford and Snow 2000; Pasquier and Wood 2018).

Third, we found dynamic adjustments in the aftermath of elections: won cases more often showed decreases in prognostic and motivational framing compared to lost cases (**RQ3**). This pattern suggests a shift in priorities once the immediate goal of winning representation is secured, with communication recalibrated from the mobilization to the consolidation phase. Such recalibration aligns with broader

theories on organizational life cycles of social movements, considering transitions from mobilization to institutionalization (Christiansen 2009; Tarrow 2022).

Together, these findings connect directly to longstanding debates about revitalization of labor unions. Scholars have argued that unions must adapt not only organizationally but also communicatively (Milkman 2013), experimenting with innovative repertoires (Juravich and Bronfenbrenner 1998; Voss and Sherman 2000). By systematically distinguishing between the communication practices around successful and unsuccessful election outcomes, our study suggests that strategic framing may be an important part of these adaptation processes. More broadly, we show the value of micro-level, comparative framing analysis for advancing our understanding of how movements strategize and evolve in the digital era. It is important to note, however, that these conclusions are drawn from observational, correlational analyses and predictive modeling; as such, they do not support causal claims about the effects of specific framing strategies on election outcomes.

Limitations, Implications and Future Work While our study makes both methodological and substantive contributions, several limitations should be noted. First, our data is observational and correlational; consequently, observed associations between communication features and electoral success cannot be interpreted causally. In particular, framing may reflect underlying organizational capacity rather than independent strategic choice: unions with greater resources, stronger leadership, or more intensive offline organizing may both communicate differently and be more likely to win elections. Second, the analysis is limited to Facebook, an important but partial element of unions' communication strategies, which also involve other digital platforms and offline channels. Out of over 500 unions with available election outcomes, only 66 had Facebook accounts, and only 40 provided downloadable data, resulting in a relatively small and potentially skewed sample. Consequently, our findings may not generalize to all unions, particularly those for which Facebook is not a primary communication channel. Third, our analysis focuses on posts from the week immediately before and after each election. While this window is intended to capture communication tied to electoral events, it may be too narrow to reflect longer-term framing strategies or too broad, capturing stable communication patterns rather than election-specific adjustments. To mitigate the latter concern, we account for longer-term trends in frame usage by leveraging periods without elections. Fourth, we focus on national and international level union accounts to ensure sufficient activity, which may obscure dynamics in smaller or more localized organizations. Changes in data access policies could allow for analyses that can estimate the impact of such issues. Fifth, we analyzed five discourse frames identified in prior work on social movements and civil society organizations. This enhances comparability but may overlook additional frames or nuances. Finally, unions differ in size, resources, and political context, factors likely shaping communication in ways not fully accounted for here. We also acknowledge that systematic analyses of union communica-

tion could be misused by political actors, employers, or other organizations, underscoring the need for careful ethical reflection when applying these methods.

Despite these limitations, the study has implications for multiple audiences. For labor unions, the findings can inform digital communication strategies, highlighting how different frames can be used in election campaigns. For political communication researchers, the study offers large-scale empirical evidence on how civil society organizations employ framing online. For organizations more broadly, our results suggest ways to refine messaging to balance mobilization, solidarity, and engagement objectives. Methodologically, the released classifier and dataset provide a scalable resource for studying digital discourse framing across movements.

Future work could extend this study in several directions. Expanding the frame taxonomy would allow more fine-grained analyses of communication strategies, including issue-specific frames. Examining union accounts at smaller, local levels—beyond the national and international accounts analyzed here—could reveal additional variation in messaging. Multi-platform analyses would provide a more holistic picture of unions' communication ecosystems beyond Facebook. Incorporating a perspective on the targets of unions' communication would also provide a broader understanding of strategic efforts and complement existing literature that suggests ad hoc targeting as one valuable revitalization strategy (Earl 2019; Uba and Jansson 2021). Finally, incorporating audience responses through engagement metrics and comments would help link message production with resonance, offering deeper insight into the interplay between framing practices and collective action dynamics.

Related Work

NLRB Election Data

The National Labor Relations Board (NLRB) election data has been widely used to study unionization dynamics in the United States, particularly predictors of union success. Early work by Maranto and Fiorito (1987) highlights union size, internal democracy, strike activity, and centralized decision-making as key determinants of certification outcomes. Extending this perspective, Ferguson (2008) models organizing as a sequential process from petitions to first contracts, highlighting union size and unfair labor practice charges as critical across stages.

A second strand of studies combines NLRB data with external sources to investigate how broader institutional and demographic contexts shape unionization. For example, Sojourner and Yang (2022) connects certification to workplace safety enforcement, while Ferguson (2015) studies workplace composition using Equal Employment Opportunity Commission data. Bronfenbrenner (2005) takes a related approach by comparing bargaining units across gender compositions, assessing the role of company characteristics, union demographics, and organizing tactics.

Other studies situate elections within broader political-economic dynamics. Stepan-Norris and Southworth (2010) analyzes inter-union competition, while Schaller (2023)

links union decline to sectoral and regional shifts. Finally, Ferguson, Dudley, and Soule (2018) connects labor organizing to wider social movements, introducing the concept of *osmotic mobilization* to demonstrate how protest activity in society at large correlates with support for unions in representation elections.

This literature demonstrates the versatility of NLRB election data for analyzing both the internal dynamics of organizing and its intersection with external institutional, demographic, and political factors. While prior work focuses on predictors of success, workplace outcomes, and long-term trends, we incorporate the digital domain, using NLRB data to anchor the analysis of online communication.

Digital Communication of Labor and Social Movements

Labor Movement With the widespread adoption of digital technologies, labor unions increasingly use online platforms to engage members, recruit participants, and communicate with stakeholders. Union strategies are shaped by both external political contexts and internal organizational choices (Martínez Lucio 2003). Among revitalization strategies, *organizing*—recruiting, representing, retaining members, and expanding mobilization capacity—is particularly prominent in digital settings (Frege and Kelly 2004). Communication plays a central role in these efforts, as discourse frames help articulate grievances, propose solutions, and mobilize collective identities.

A substantial body of work links framing to labor organizing. Building on collective action theory (Snow, Benford et al. 1988), Kelly (1998) argues that successful mobilization depends on workers perceiving injustice, identifying solutions, and believing in collective efficacy. Similarly, Voss and Sherman (2000) highlights the importance of identifying the right strategic repertoires of communication and engagement for the labor revitalization efforts to be successful. Other foundational work that followed highlights the importance of identifying the right frames for women and minorities (Bronfenbrenner 2005), and millennials (Milkman 2013).

Research on digital communication has largely focused on mobilization. Studies of the Fight for Fifteen movement show how social media supports mobilization and connects collective action with grassroots dynamics (Pasquier and Wood 2018; Pasquier, Daudigeos, and Barros 2020; Frangi, Zhang, and Hebdon 2020). Other work analyzes mobilizing frames across platforms (Houghton and Hodder 2021), coding social media posts in terms of framing, attribution, and calls to action. Beyond mobilization, research has also examined how digital networks support organizational purposes, such as building collective voices prior to mobilization (Lazar, Ribak, and Davidson 2020), or reaching marginalized groups otherwise excluded from traditional organizing channels (Wood 2015; Thornthwaite, Balnave, and Barnes 2018). The effectiveness of communication strategies is also contingent on other important factors, such as organizational and leadership structures, as demonstrated in the comparative analysis of 2018 teachers' strikes in Oklahoma and Arizona (Blanc 2022).

Despite these insights, evidence suggests that unions are not fully exploiting the potential of digital media. Hodder and Houghton (2020) finds that online campaigning and news reporting remain dominant uses, leaving recruitment opportunities largely untapped. Likewise, Carneiro and Costa (2022) documents outdated strategies centered on one-way information sharing, rather than fostering engagement. More promising results emerge when unions tailor their communication to specific worker groups (Jansson and Uba 2019) and account for the diversity of audiences with distinct communication needs (Panagiotopoulos 2021). These targeted strategies appear to be a necessary step towards building more effective digital communication.

Beyond the Labor Movement Beyond unions, a large body of research examines how social movements and civil society organizations use digital platforms to structure collective action and mobilize supporters.

One line of work emphasizes the role of *mobilization frames* in online environments. Building on framing theory, scholars show how social media enables the diffusion of diagnostic, prognostic, and motivational frames, crucial for lowering barriers to participation (Benford and Snow 2000; Fernández-Zubieta et al. 2023; Mendelsohn et al. 2024; Pera and Aiello 2025). A second perspective highlights the shift from the *logic of collective action* toward the *logic of connective action* (Bennett and Segerberg 2012). While traditional mobilization relies on formal organizations and collective identities, connective action underscores personalized, digitally mediated participation that can occur without strong organizational structures. This framework has been applied to cases such as the Arab Spring (Steinert-Threlkeld 2017) and climate activism (Segerberg and Bennett 2011). Finally, research on digital *affordances* investigates how platform features—such as sharing content, meta-voicing, and multimedia storytelling—shape the opportunities and constraints of collective action (Zheng and Yu 2016; Sæbø, Federici, and Braccini 2020).

While prior research has provided valuable insights into social media mobilization and organizational communication, many studies rely on qualitative analyses or selected use cases. In contrast, our study leverages a large-scale computational approach to systematically examine union social media communication during times of representation elections at the micro-level of individual messages. Moreover, by linking communication patterns to NLRB election outcomes, we explore how online framing relates to tangible organizational success, providing empirical evidence on the functional value of digital strategies that complements existing theoretical and qualitative work.

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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](#).
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes](#).
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? [Yes, in the "Methodological Framework" section](#).
 - (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? [Yes, we discuss potential biases in our data in the "Discussion and Conclusion" section](#).
 - (e) Did you describe the limitations of your work? [Yes, limitations are presented and discussed in the "Discussion and Conclusion" section](#).
 - (f) Did you discuss any potential negative societal impacts of your work? [Yes, we address negative societal impact in the "Discussion and Conclusion" section](#).
 - (g) Did you discuss any potential misuse of your work? [Yes, we discuss potential misuse in the "Discussion and Conclusion" section](#).
 - (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 share the steps and our framework in the "Methodological Framework" section. Full experimental details \(code\) are provided as a shared repository](#).
 - (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes](#).
2. Additionally, if your study involves hypotheses testing...
 - (a) Did you clearly state the assumptions underlying all theoretical results? [Yes, we frame our experiments within the scope of previous research in the "Theoretical Framework", "Methodological Framework", and "Related Work" sections](#).
 - (b) Have you provided justifications for all theoretical results? [Yes, justifications are provided in the "Results" and "Discussion and Conclusion" sections](#).
 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? [Yes, other approaches in terms of theoretical frameworks and the motivation behind our choice are described in the "Methodological Framework" and the "Related Work" sections](#).
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? [Yes, in the "Results" and "Discussion and Conclusion" sections we explore potential confounders of our results and highlight limitations of our work](#).
 - (e) Did you address potential biases or limitations in your theoretical framework? [Yes, these are addressed in the "Discussion and Conclusion" section](#).
 - (f) Have you related your theoretical results to the existing literature in social science? [Yes, we directly relate our work to previous work in "Introduction", "Related Work", and "Theoretical Framework"](#).
 - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? [Yes, these are discussed in the "Discussion and Conclusion" 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)? [Yes. Included link to shared repository \(see "Introduction"\)](#). Configuration details are reported in Appendix.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes, whenever necessary. Described in "Methodological Framework" and Appendix. Details are given in the code provided in the shared repository](#).
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes, whenever relevant. Specifically, we took into account confidence intervals in Figures 3 and 4 in the main text and in robustness checks reported in the Appendix](#).
 - (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, see reference to computational resources in "Methodological Framework" and details in the Appendix](#).
 - (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? [Yes, specified in the "Methodological Framework" and "Results" section](#).
 - (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? [Yes, in the "Results" section](#).
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? [Yes, creators of models used as part of the experiments are cited in "Methodological Framework" section](#).
 - (b) Did you mention the license of the assets? [Yes, see Appendix](#).
 - (c) Did you include any new assets in the supplemental material or as a URL? [Yes, data and code are included in the shared repository linked in the "Introduction"](#).

- (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? [Our data contains PII of labor unions in the United States. We discuss this in the DataSheet \(Supplementary Material\).](#)
 - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? [Yes, see DataSheet in the Supplementary Material.](#)
 - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see Gebru et al. (2021))? [Yes, see the Supplementary Material.](#)
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.

A Frames Annotation

We annotated Facebook posts for the presence of five discourse frames: *diagnostic*, *prognostic*, *motivational*, *community*, and *engagement*. In addition, given the close ties between labor unions and political events (e.g., presidential elections, support for congressional candidates), we also annotated posts with an auxiliary label: *political endorsement*. This label captures instances in which unions explicitly support political actors or candidates.

The complete annotation guidelines are provided in the supplementary material (`codebook.pdf`).

B Modeling and Computational Details

We fine-tuned a RoBERTa-base model to capture the characteristics of unions’ Facebook communications. For this fine-tuning of the language model, we used 5 epochs with a batch size of 128, keeping all other parameters at their default values. Training was performed on a Tesla V100 GPU and required about 30 minutes.

For the multi-label classification task, we trained the RoBERTa model for 30 epochs with a learning rate of 4×10^{-5} and a batch size of 32. To address class imbalance, we applied class weights computed as

$$\frac{\text{total samples}}{2 \times [n_{\text{class } 0}, \dots, n_{\text{class } n}]}$$

All other parameters were left at default settings. Training required a few minutes on a Tesla V100.

We also evaluated a BERT-base uncased model that underwent the same fine-tuning pipeline and resulted in similar computational costs.

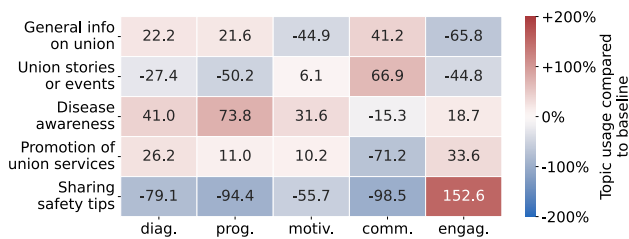
The multi-label classification setup included the five main discourse frames and the additional *political endorsement* label. However, given the very limited presence of political endorsement in the annotated dataset (3% of posts across training and test sets) and in the full Facebook dataset (2.5% of posts), we did not retain this label in the main analysis. We therefore focus exclusively on the five core discourse frames in the paper.

B.1 Licenses

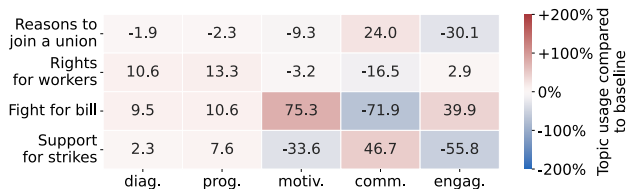
The RoBERTa base model used for building the multi-label communication frames classifier is licensed under a MIT license. The BERT-base model used as a comparison is licensed under an Apache License, Version 2.0. The emotion classification model is licensed under an Apache License, Version 2.0.

C Topic Modeling on Selected Unions

To explore the relationship between topics and frames, we examined posts from two of the most active (i.e., by total number of posts) craft and industrial unions on Facebook, namely IAFF and SEIU. Using topic modeling through BERTopic, we analyzed their posts in terms of prevalent topics. Figure C1 presents manually merged, overarching topics that appear in at least 5% of posts, showing how the prevalence of each topic within a frame deviates from its overall usage.



(a) IAFF (Craft)



(b) SEIU (Industrial)

Figure C1: Usage of topics within posts with a given frame relative to overall topic usage. Cell values represent percentages; red indicates higher-than-baseline usage, blue indicates lower-than-baseline usage.

In the main text, we pointed at the fact that applying topic modeling across all posts resulted in many union-specific topics. Even at the union level, some topics remain highly specific—for example, *sharing safety tips* for IAFF. Certain topics align with particular frames: in IAFF, *union stories or events* is more common in posts using the *community* frame, while *sharing safety tips* appears more often in the *engagement* frame. In SEIU, *reasons to join a union* and *support for strikes* are more often associated with *community* frames. At the same time, many topics, such as IAFF’s *general info on union* or SEIU’s *rights for workers* and *fight for bill*, cut across frames without a single dominant association.

Overall, topic modeling is useful for capturing additional nuance within frames, highlighting the specific issues discussed. However, its highly union-specific nature limits its usefulness for generalizable predictions beyond frame-level analysis.

D Robustness Checks

D.1 Alternative Classifiers

We considered two alternative classifiers in to compare with the RoBERTa-base one fine-tuned on language and then on labeled data, referenced in the main text. The first is a RoBERTa-base classifier simply fine-tuned on the labeled data, skipping the language fine-tuning step. We report its performance on the test set in Table D1.

The second is a BERT-base uncased model, fine-tuned on language across all Facebook posts and then on the labeled data for multi-label classification. We report its performance in Table D2.

Frame	Precision	Recall	F1-score	Support
Diagnostic	0.77	0.86	0.81	84
Prognostic	0.70	0.72	0.71	58
Motivational	0.59	0.83	0.69	29
Community	0.67	0.72	0.69	81
Engagement	0.72	0.82	0.77	51
Micro avg	0.70	0.79	0.74	303
Macro avg	0.69	0.79	0.73	303
Weighted avg	0.70	0.79	0.74	303

Table D1: Performance of the multi-label discourse frames classifier (RoBERTa-base, just fine-tuned for the classification task).

Frame	Precision	Recall	F1-score	Support
Diagnostic	0.80	0.82	0.81	84
Prognostic	0.67	0.62	0.64	58
Motivational	0.58	0.66	0.61	29
Community	0.62	0.65	0.63	81
Engagement	0.62	0.67	0.64	51
Micro avg	0.67	0.70	0.68	303
Macro avg	0.66	0.68	0.67	303
Weighted avg	0.67	0.70	0.68	303

Table D2: Performance of the multi-label discourse frames classifier (BERT-base uncased, fine-tuned for language and then fine-tuned for the classification task).

D.2 Coding Diagnostic and Prognostic in a Single Category

The predictive power of frames over election winning is robust to the coding of diagnostic and prognostic into a single category rather than considering them as separate predictors. The only exception is disgust, whose posterior distribution excludes zero in fewer than six out of ten model runs when diagnostic and prognostic frames are modeled separately, indicating sensitivity to model specification rather than a robust association. Figures D1 and D2 illustrate this pattern for models including only the proportion of diagnostic and prognostic posts prior to the election, respectively.

D.3 Window Size for Aggregation

The estimated effects of diagnostic and prognostic frames on election outcomes remain stable across alternative aggregation window sizes. In contrast, the posterior distribution for community framing increasingly overlaps zero, indicating reduced evidence for an association under this specification. The estimated effect of neutral emotional content remains robust across window sizes. Random intercepts for states are largely stable, with the exception of Arizona, whose posterior distribution is shifted toward higher baseline odds of winning in this configuration (cf. Figure D3).

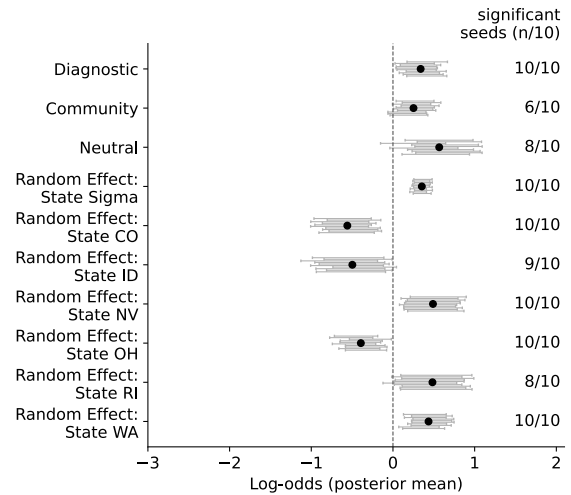


Figure D1: Posterior mean log-odds estimates across ten seeds, not considering the proportion of prognostic frames in the predictors. Variables not shown had no credible association with the outcome or credible association for fewer than six seeds.

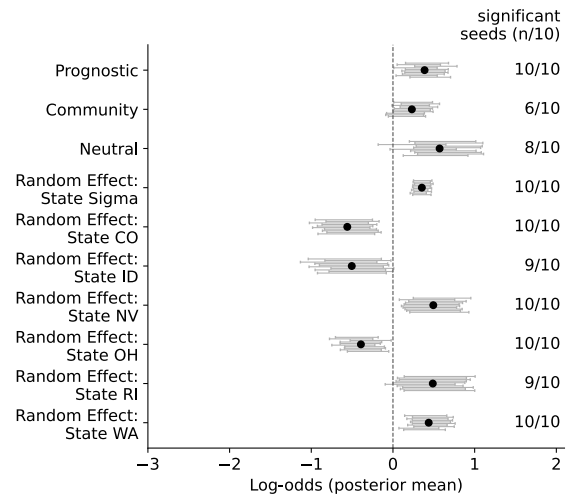


Figure D2: Posterior mean log-odds estimates across ten seeds, not considering the proportion of diagnostic frames in the predictors. Variables not shown had no credible association with the outcome or credible association for fewer than six seeds.

D.4 Imbalance for Number of Cases per Union

Frames Usage Leading to Elections In the main paper, we already demonstrated the robustness of coefficient estimates to different random seeds used to balance wins and losses within unions.

We next assess robustness to variation in the number of representation cases per union. Specifically, we capped the total number of cases per union at the 90th percentile of the distribution (considering winning and losing outcomes

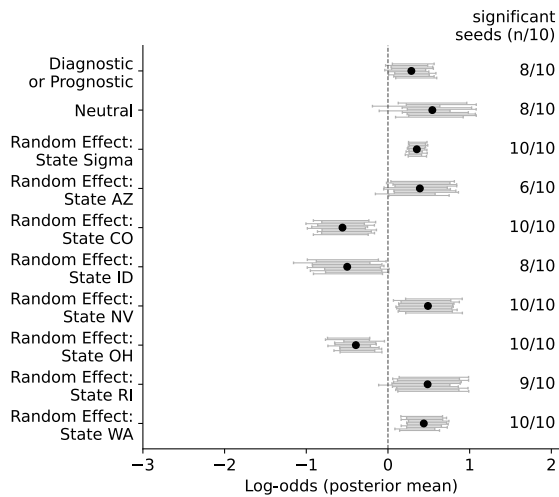


Figure D3: Posterior mean log-odds estimates across ten seeds, considering a window of three days for aggregation. Variables not shown had no credible association with the outcome or credible association for fewer than six seeds.

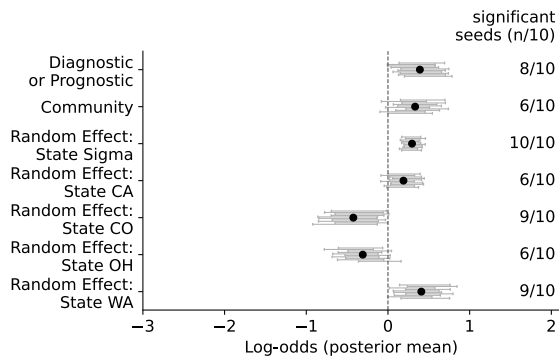


Figure D4: Posterior mean log-odds estimates across ten seeds, downsampling over-represented unions.

jointly) and repeated the analyses across ten random seeds. For each seed, we first balanced the number of wins and losses per union and then fitted a Bayesian logistic regression model predicting the binary election outcome.

Figure D4 presents posterior log-odds estimates for selected model variables. Overall, the results are robust to differences in the number of representation cases across unions. Estimated effects of diagnostic/prognostic and community frames remain stable, whereas posterior distributions for disgust-related and emotionally neutral content increasingly overlap zero under this specification. State-level random intercepts are largely consistent across models, with Colorado, Ohio, and Washington exhibiting similar deviations from the global intercept, while California's posterior distribution is shifted toward higher baseline odds of winning.

Frames Usage Pre- and Post-Elections Given that we balanced the number of wins and losses per union, we verified the robustness of results to the choice of random seed

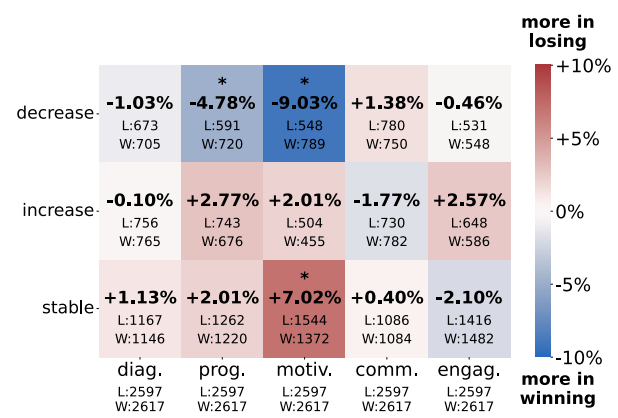


Figure D5: Usage of frames before and after the event, comparing lost and won cases. The \star sign indicates a significant difference between outcome types ($p < 0.05$).

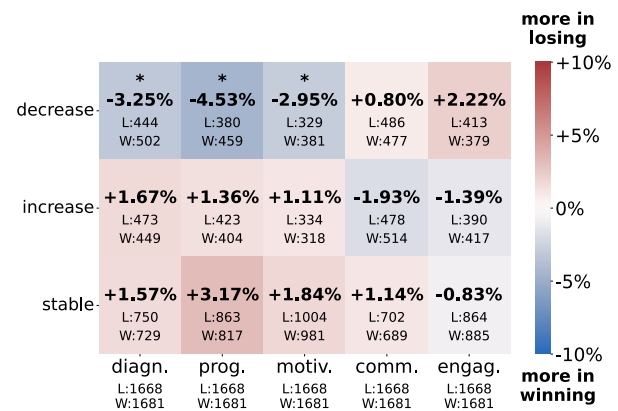


Figure D6: Usage of frames before and after the event, comparing lost and won cases. The \star sign indicates a significant difference between outcome types ($p < 0.05$).

for sampling. As such, we repeated the balancing procedure with 20 random seeds. For each combination of pattern, frame, and seed, we then computed the offset between lost and won cases (*losing* minus *winning*) and measured the significance of such an offset. In the end, we considered the average offset value across seeds for each pattern and frame combination and highlighted the offset as significant if 80% of the seeds showed a significant offset for that combination. Figure D5 summarizes these robustness results. The most relevant findings are robust: communication in won cases showed a higher frequency of decrease in *prognostic* and *motivational* frames after the election, and communication in lost cases was characterized by greater stability in the use of the *motivational* frame.

To account for potential imbalance in the number of representation cases per union, we limited the total cases per union to the 90th percentile, repeating the analyses across 20 random seeds. For each seed and frame, post-/pre-election changes were classified into three patterns: decrease, or increase. For each seed, we first balanced the number of

wins and losses per union. Then, for each combination of pattern, frame and seed, we computed the offset between lost and won cases (*losing* minus *winning*) and measured the significance of such an offset. In the end, we considered the average offset value across seeds for each pattern and frame combination and highlighted the offset as significant if 80% of the seeds showed a significant offset for that combination. Figure D6 summarizes these robustness results. While not all patterns remain significant under this procedure, the most relevant findings are robust: communication in won cases showed a higher frequency of decrease in *prognostic* and *motivational* frames after the election.

E Details on Labor Unions

Table E1 reports the full names unions considered in the study. Figure E1 shows the distribution of the number of Facebook posts per union.

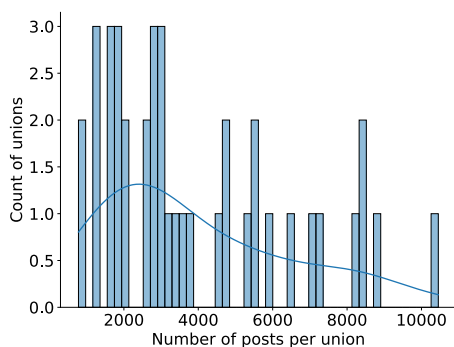


Figure E1: Number of Facebook posts by labor union.

Acronym	Expanded Name	Union Structure
RWDSU	Retail, Wholesale and Department Store Union	Industrial
UAW	United Automobile Workers	Industrial
IBEW	International Brotherhood of Electrical Workers	Craft
AFT	American Federation of Teachers	Industrial
NATCA	National Air Traffic Controllers Association	Craft
IFPTE	International Federation of Professional and Technical Engineers	Industrial
AFSCME	American Federation of State, County and Municipal Employees	Industrial
NNU	National Nurses United	Industrial
IUPAT	International Union of Painters and Allied Trades	Craft
Ironworkers	International Association of Bridge, Structural, Ornamental and Reinforcing Iron Workers	Craft
NEA	National Education Association	Industrial
UMWA	United Mine Workers of America	Industrial
AFGE	American Federation of Government Employees	Industrial
IATSE	International Alliance of Theatrical Stage Employees	Craft
UFCW	United Food and Commercial Workers	Industrial
SIU	Seafarers International Union of North America	Industrial
SEIU	Service Employees International Union	Industrial
SAG-AFTRA	Screen Actors Guild – American Federation of Television and Radio Artists	Craft
BCTGM	Bakery, Confectionery, Tobacco Workers and Grain Millers	Industrial
APWU	American Postal Workers Union	Industrial
UWUA	Utility Workers Union of America	Industrial
BAC	Bricklayers and Allied Craftworkers	Craft
SMART	Sheet Metal, Air, Rail and Transportation Workers	Craft
AFM	American Federation of Musicians	Craft
CWA	Communications Workers of America	Industrial
USW	United Steelworkers	Industrial
UNITE HERE	Unite Here Union	Industrial
IAM	International Association of Machinists and Aerospace Workers	Industrial
IBT	International Brotherhood of Teamsters	Industrial
UA	United Association of Journeymen and Apprentices of the Plumbing and Pipe Fitting Industry	Craft
TWU	Transport Workers Union of America	Industrial
IAFF	International Association of Fire Fighters	Craft
ATU	Amalgamated Transit Union	Industrial
IBB	International Brotherhood of Boilermakers, Iron Ship Builders, Blacksmiths, Forgers and Helpers	Craft
Roofers	United Union of Roofers, Waterproofers and Allied Workers	Craft
LIUNA	Laborers' International Union of North America	Craft
WGAE	Writers Guild of America East	Craft
OPEIU	Office and Professional Employees International Union	Industrial
CSEA	Civil Service Employees Association	Industrial
MEBA	Marine Engineers' Beneficial Association	Craft

Table E1: Union acronyms, expanded names, and organizational structure (Craft vs. Industrial).