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High-Visibility Protest Engagement on Twitter: How Content, Form, and Event Context Interact in Thai Digital Activism

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Abstract

Research on digital protest often treats visibility and engagement as temporally uniform by aggregating social media activity across extended periods. This approach obscures how political moments shape which messages become widely amplified. Addressing this event-contingent visibility problem, this study examines how event context structures patterns of visibility in protest communication on Twitter within a semi-authoritarian media environment. Using a high-visibility corpus of the most-retweeted tweets from 21 major political protest events in Thailand during 2021, the study combines thematic content analysis with a four-way ANOVA to analyze how event context, content themes, media formats, and posting time interact to shape retweet visibility. Visibility is conceptualized not as a stable behavioral tendency but as a contingent outcome shaped by political salience, affective alignment, and platform affordances. The findings show that event context accounts for the largest share of variance in retweet visibility, while the effects of content themes and media formats are conditional and event-dependent. These results indicate that visible connective action is episodic and that affective amplification operates in context-sensitive ways. The study refines theories of digital protest by conceptualizing visibility as an event-contingent process and highlights the analytical value and limits of high-visibility sampling.

Keywords: digital protest; event-contingent visibility; high-visibility Twitter engagement; affective publics; Thai political activism

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1. Introduction

Over the past decade, Thailand has experienced recurrent cycles of political unrest, constitutional uncertainty, and tightening state control over dissent (Kongkirati & Kanchoochat, 2018; Sombatpoonsiri, 2021). These dynamics, characteristic of semi-authoritarian governance, have reshaped how citizens engage in political expression and mobilization. As street protests became increasingly constrained—whether through legal restrictions, pandemic-related limitations, or escalating repression—digital platforms emerged as critical alternative arenas for public deliberation. Twitter, in particular, played a defining role during the 2020–2021 protest waves, enabling rapid circulation, emotional expression, and real-time witnessing that would have been difficult under traditional media constraints (Sinpeng, 2021; Tufekci, 2017). Through its affordances for immediacy, visibility, and amplification, the platform shaped how unfolding political events were interpreted, contested, and redistributed.

These dynamics reflect broader global patterns in which publics negotiate political meaning through high-velocity flows of shared content. Prior research shows that emotionally charged messages tend to diffuse more widely, shaping the rhythm and intensity of online engagement during moments of political crisis (Brady et al., 2017; Stieglitz & Dang-Xuan, 2013). In Thailand, these patterns materialized vividly during high-stakes protest events—such as police confrontations, symbolic court rulings, or parliamentary milestones—each generating distinct waves of amplification as users documented injustice, expressed solidarity, or circulated political messaging (Sinpeng, 2021; Sombatpoonsiri, 2023; Charoenthansakul & Natee, 2023; Phoborisut, 2021). Event-driven surges in visibility thus became a hallmark of Thailand's digital protest ecology: attention did not accumulate uniformly over time but fluctuated sharply in response to the salience, emotional charge, and perceived risk embedded within specific political moments (Brady et al., 2017; Sinpeng, 2021). These patterns point to an overlooked conceptual issue: visibility in digital protest is not a stable attribute of messages but a contingent process triggered by shifts in political and emotional intensity.

Yet, despite growing scholarly interest in digital activism and connective action (Bennett & Segerberg, 2012), the explicit influence of event context on message visibility remains conceptually underdeveloped. Much existing research aggregates social media data across extended periods, treating engagement as a stable behavioral tendency rather than a dynamic, context-sensitive response to specific events. This flattening obscures how publics recalibrate their attention and emotional investment as political conditions shift. Similarly, scholarship frequently analyzes large random samples or hashtag corpora without distinguishing between widely amplified messages and the broader information stream. However, high-visibility content—posts that achieve significant reach—often plays a disproportionate role in shaping collective interpretation and public discourse (Papacharissi, 2015; Highfield, 2016). High-visibility tweets can function as agenda-setting signals within affective publics, influencing how events are interpreted and circulated beyond their immediate audiences. Finally, studies of visibility overwhelmingly focus on Western democratic contexts. Far less is known about how visibility emerges under semi-authoritarian conditions, where censorship, surveillance, and political volatility impose distinctive pressures on communicative practices (King et al., 2013; Sinpeng, 2021). Taken together, these gaps constitute what we refer to as the event-contingent visibility problem: the limited theorization of how political moments condition which messages become widely amplified.

Against this backdrop, this study asks a focused empirical question: how does event context structure the visibility of protest communication on Twitter? To address this question, the study analyzes a high-visibility corpus consisting of the 100 most-retweeted tweets from each of 21 major political protest events in Thailand during 2021. While such messages do not represent the full ecology of protest communication, they provide a theoretically meaningful lens on the forms of expression, narrative framings, and affective signals that publics chose to amplify most strongly during moments of heightened salience. Visibility, understood here as an outcome of collective engagement shaped by emotional resonance, platform affordances, and algorithmic prioritization, is not simply a property of message content but a relational process emerging from interactions between publics, algorithms, and event-driven political conditions (Brady et al., 2017; Highfield, 2016). Accordingly, the findings speak specifically to the dynamics of high-visibility counterpublic discourse, rather than to the full distribution of protest communication across the platform.

Using thematic coding and a four-way ANOVA, this study examines how event context, content themes, media formats, and posting time jointly shape retweet visibility within this high-engagement corpus. Rather than conceptualizing engagement as a generalized behavioral metric, the analysis foregrounds visibility as contingent—structured by the salience of the political moment and by affective publics' responses to rapidly evolving conditions. This event-sensitive approach aligns the methodological design with the study's central aim: assessing mean differences in visibility as conditioned by multiple interacting factors, an analytical logic well suited to ANOVA.

Guided by these concerns, the analysis is organized around two research questions:

RQ1: How does event context influence the visibility of high-engagement protest tweets in Thailand?
RQ2: To what extent do content themes, media formats, and posting time influence retweet visibility, and are these effects dependent on specific protest events?

This study offers three core contributions. First, it demonstrates empirically that event context accounts for the largest share of variance in visibility, underscoring how collective attention is unevenly organized around moments of heightened salience and emotional intensity. Second, it extends scholarship on affective publics by showing how visual media and emotionally expressive content amplify engagement under semi-authoritarian conditions where digital repression shapes communicative behavior. Third, it advances methodological discussions by elaborating the conceptual value—and limitations—of high-visibility sampling for analyzing protest communication. Together, these contributions refine theoretical understandings of digital activism, event-driven visibility, and contextualized political communication, while positioning Thailand as a theoretically generative case for examining how publics amplify and interpret political events within constrained media environments.

2. Literature Review

2.1. Platform Visibility, Algorithmic Amplification, and the Politics of Selection

Visibility on social media is shaped not merely by user practices but by socio-technical infrastructures that govern what becomes amplified, searchable, and politically consequential. Platforms such as Twitter—through algorithmic curation, ranking, and recommendation systems—operate as gatekeepers that structure the circulation of information (Gillespie, 2014; Bucher, 2018). Retweet volume becomes both an indicator of public resonance and a feedback signal that increases the likelihood of further algorithmic amplification. As Highfield (2016) and Boyd (2010) observe, highly visible posts disproportionately influence political interpretation and public agendas because they crystallize issue salience within networked publics. At a systemic level, visibility follows power-law distributions: only a small fraction of posts receives most engagement (Bakshy et al., 2011). This inequality reflects what Brady et al. (2017) describe as "selection mechanisms," where algorithmic privileging interacts with affective intensity, clarity of framing, and media format to determine which messages gain momentum. Algorithmic timelines, optimized for engagement, tend to amplify emotionally charged content, thus shaping the visibility of political discourse in ways that are not ideologically neutral (Bucher, 2018; Gillespie, 2014).

Platform visibility takes on heightened political significance within contentious environments. High-visibility tweets can condense dispersed sentiments during protests, frame the emotional tone of a moment, and serve as anchors around which collective meaning is negotiated (Papacharissi, 2015). As Tufekci (2017) notes, the ability of platforms to make certain forms of witnessing visible—particularly images and videos of confrontations—shapes the broader public understanding of unfolding events. While prior research highlights how algorithms amplify political content, most empirical studies treat engagement as temporally uniform, aggregating data across long periods rather than analyzing how visibility fluctuates across discrete events. Additionally, studies often rely on large hashtag corpora or random samples that obscure the subset of highly amplified posts that most strongly influence public discourse. High-visibility sampling therefore provides a theoretically meaningful approach for understanding how publics respond to political turbulence and how platform logics shape the circulation of protest communication.

In semi-authoritarian settings such as Thailand, the politics of visibility intersect with state regulation and risk. King et al. (2013) demonstrate how authoritarian states strategically tolerate low-risk criticism while suppressing collective expression—an insight directly relevant to understanding why some protest-related tweets become widely amplified while others remain less visible. Thus, visibility emerges not only from platform mechanisms but also from the political environment in which digital communication unfolds. These platform-level dynamics underscore that visibility is not a static attribute of content but a relational process shaped by interactions among users, algorithms, and situational political conditions—particularly salient during rapidly unfolding protest events.

2.2. *Affective Publics, Emotional Amplification, and Networked Mobilization*

A second body of scholarship emphasizes the emotional and affective dimensions of digital political participation. Papacharissi's (2015) concept of affective publics describes how emotions—anger, grief, hope, and fear—circulate across networks and shape political discourse by attaching intensity and meaning to specific events. Emotional expression online fosters solidarity, signals identity, and mobilizes collective action (Papacharissi, 2015; Tufekci, 2017). Affective expression is also a powerful visibility mechanism. Studies consistently show that moralized anger and emotionally charged content diffuse more widely than neutral messages because they activate psychological and social motivations to share (Brady et al., 2017). Stieglitz and Dang-Xuan (2013) further find that sentiment intensity predicts information diffusion on microblogging platforms, demonstrating the central role of affect in visibility dynamics.

In contexts of repression, emotion and visibility become even more tightly intertwined. In Thailand's semi-authoritarian environment, users often navigate political risk by calibrating emotional expression, balancing solidarity with caution (Sinpeng, 2021). Outrage toward police violence, fear of repression, and grief after symbolic events frequently produce rapid waves of sharing that crystallize collective grievances (Phoborisut, 2021). Here, visibility is not simply a reaction to emotional content but a strategy of political engagement shaped by risk perceptions. Affective publics respond strongly to event salience. High-stakes moments—court rulings, violent confrontations, or political deadlocks—generate distinct affective signatures that drive spikes in engagement. Yet such waves vary significantly across events, reflecting not only emotional dynamics but the situational conditions of each protest moment. This variability suggests that visibility cannot be understood without accounting for event context.

Thailand-specific scholarship reinforces this point. Charoenthansakul and Natee (2023), examining highly retweeted tweets from the 2020 protest movement, show that emotional expressions and symbolic messages played a central role in driving visibility. Their findings underscore that affective publics in Thailand operate under constraints shaped by repression, social polarization, and generational divides. Despite substantial work on emotion and digital activism, few studies analyze how affective expression interacts with event context to shape visibility. Even fewer explore this relationship within high-visibility corpora—precisely where affective amplification is most pronounced. Importantly, visibility should not be equated with affect itself; rather, it reflects how affective cues, platform incentives, and contextual pressures converge to shape amplification. This distinction is useful for interpreting visibility metrics in politically constrained environments.

2.3. Event-Contingent Connective Action: Salience, Repression, and Media Witnessing

Digital protest communication is profoundly structured by events. Connective action theory (Bennett & Segerberg, 2012) emphasizes personalized, digitally mediated participation, but scholarship has recently turned toward understanding how discrete events shape communication patterns, risk dynamics, and public attention. Events are not mere chronological markers; they are affective and political configurations that vary in salience, symbolic meaning, and perceived risk. Public attention is therefore highly event-dependent, with crises, confrontations, and symbolic milestones generating distinct surges in engagement. During such moments, practices of media witnessing—such as sharing images, videos, or first-person accounts—become central to how publics interpret unfolding events (Tufekci, 2017). Hermida et al. (2014) further demonstrate how Twitter functioned as a critical sourcing infrastructure during the Tunisian and Egyptian revolutions, enabling real-time documentation and witnessing under conditions of media constraint and state censorship. More broadly, studies of the Arab Spring show that moments of crisis, confrontation, and regime violence generated sharp surges in online engagement, as citizens and activists used social media to document unfolding events, circulate emotionally charged narratives, and bear witness to state actions (Howard & Hussain, 2013; Tufekci & Wilson, 2012). During these high-salience moments, media witnessing played a central role in shaping collective interpretation and symbolic coordination across networked spaces.

Repression interacts with event dynamics in complex ways. In Thailand, where legal risks, surveillance, and punitive measures constrain participation, individuals rely heavily on digital communication to document state actions, amplify narratives, and negotiate political identity (Sinpeng, 2021). Repression can suppress participation but also catalyze visibility through outrage, fear, or moral shock. Political science research situates these dynamics within Thailand's broader authoritarian structure. Kongkirati and Kanchoochat (2018) describe how hierarchical capitalism and military–bureaucratic control shape political contestation, while Sombatpoonsiri (2021, 2023) demonstrates how civic networks, repression, and polarization influence mobilization and counter-mobilization. These studies underscore that protest communication in Thailand unfolds within a field of constrained expression and politicized risk.

Although prior research has advanced important insights into framing, repression, and mobilization dynamics, studies have yet to examine how event context interacts simultaneously with message content and media format to shape visibility within protest communication. This gap is particularly notable given that event conditions influence levels of risk, emotional intensity, and public attention; message content shapes the meanings and narratives available to publics; and media formats affect the communicative affordances that drive amplification. Despite the theoretical significance of these interdependencies, empirical analyses have rarely treated these dimensions as mutually shaping factors, especially within high-visibility protest communication in semi-authoritarian environments. Taken together, these three bodies of scholarship demonstrate that visibility in digital protest communication cannot be reduced to platform dynamics, emotional expression, or event characteristics alone. Instead, visibility emerges from the interaction of these forces, particularly in semi-authoritarian environments where political risk conditions shape both expression and amplification. These patterns suggest that event context may moderate how content features and media formats shape visibility, pointing to the value of analytical approaches capable of identifying interaction effects—not merely independent associations.

2.4. Integrating the Three Pillars: Conceptual Framework for the Present Study

The three strands of literature discussed above collectively indicate that visibility in digital protest communication emerges from the convergence of platform architectures, affective dynamics, and event-specific political conditions. Building on these insights, the present study develops a conceptual framework that treats visibility not as a stable behavioral property but as a contingent outcome shaped by the interaction of publics, platforms, and political contexts. First, visibility is platform-dependent, structured by algorithmic prioritization and engagement-driven amplification. Second, it is affect-driven, as emotional expression within networked publics determines which messages resonate and circulate widely. Third, visibility is event-contingent, fluctuating according to the salience, symbolic meaning, and risks associated with discrete protest moments.

While each dimension has been studied independently, their interaction remains insufficiently theorized—particularly in environments shaped by digital repression. In Thailand, where legal and political risks influence how individuals express dissent, the alignment between affective publics and event salience becomes especially consequential. Individuals adjust their sharing and witnessing practices in response to political uncertainty, producing visibility patterns that vary markedly from one event to another. This integrated framework provides the conceptual grounding for the present study. It explains why event context should be treated as the organizing structure through which message features—such as content theme, media format, and posting time—acquire meaning and visibility. Rather than conceptualizing engagement as a stable behavioral metric, the framework positions visibility as an outcome that shifts across political moments as publics, platforms, and situational conditions interact.

By synthesizing platform visibility, affective publics, and event-contingent connective action, this framework advances a more contextualized understanding of digital protest communication under semi-authoritarian conditions. It highlights how high-visibility content reflects not only algorithmic and engagement-based mechanisms but also the emotional, symbolic, and political forces that shape communication during discrete events. In doing so, it strengthens broader scholarship on visibility production in politically constrained environments—particularly within Thailand's evolving protest landscape. This framework also supports the use of interaction-oriented analyses capable of examining how multiple dimensions jointly shape visibility across events. Accordingly, the empirical analysis employs a multi-factor ANOVA as one practical approach for exploring these patterned differences.

3. Methods

3.1. Research Design

This study employed a quantitative, observational, cross-sectional design using public Twitter data from protest-related communication in Thailand during 2021. Manual thematic content analysis was combined with inferential statistical techniques to examine how message characteristics and contextual factors shaped patterns of visibility. This mixed approach leverages the strengths of each method: thematic analysis captures the communicative intent embedded in tweets, while statistical modelling enables systematic comparison of visibility patterns across structural and contextual conditions. Rather than treating engagement as a stable behavioural tendency, the design is consistent with the conceptual framework in approaching visibility as a contingent outcome of interactions between content, structural features, and event-specific political conditions.

In line with the connective action framework (Bennett & Segerberg, 2012), retweeting is conceptualized as a form of affective engagement rather than a passive diffusion mechanism. Retweets both signal emotional alignment and contribute to the algorithmic amplification of shared affective frames, thereby connecting individual expressions into networked publics (Papacharissi, 2015). This analytical stance positions visibility not as a mere quantitative metric but as a communicative manifestation of affective participation under semi-authoritarian conditions.

Algorithmic amplification not only privileges content with high engagement metrics but also disproportionately surfaces emotionally resonant material, shaping the affective texture of online publics (Huszár et al., 2022; Milli et al., 2023). Accordingly, the research design reflects the assumption that social media visibility follows a power-law distribution, where attention concentrates around a limited number of highly visible posts. The analytical focus, therefore, is on those tweets that achieved high circulation, as they illuminate how affective publics crystallize around moments of political salience.

The selection of highly retweeted tweets constitutes a form of sampling on visibility. This design choice is intentional and aligned with the study's analytical objective. The purpose is not to predict absolute retweet counts or to represent the full distribution of participation on the platform, but to examine relative differences in visibility within a high-visibility subset. By focusing on tweets that already achieved substantial amplification, the analysis isolates moments where algorithmic prioritization and collective engagement are present, enabling systematic comparison of how visibility varies across events, content themes, and media formats under conditions of heightened attention. Within this design, selection on the dependent variable is unlikely to bias the specific within-sample comparisons, as the analysis focuses on conditional differences among already amplified tweets rather than population-level engagement patterns.

3.2. Data Collection and Tweet Selection

3.2.1. Data Collection Procedure

Tweets were collected using Python (version 3.10)'s snscrape library, which enabled full-year historical access beyond the seven-day limit of Twitter's public API. A predefined list of Thai protest hashtags—each corresponding to specific protest dates—served as search terms (for example, #ม็อบ10กุมภา [#Mob10Feb], #ม็อบ1สิงหา [#Mob1Aug], #ม็อบ14พฤศจิกา [#Mob14Nov]). Because hashtag practices vary considerably across protest contexts and political cultures, it is necessary to briefly clarify the rationale behind the hashtag selection strategy adopted in this study.

Unlike umbrella movement hashtags such as #BlackLivesMatter or #FridaysForFuture—which index ongoing political identities—Thai protest hashtags function mainly as date-specific event markers. During the 2020–2021 pro-democracy protests, activists frequently used hashtags combining a date and event label (for example, #28FebMob, #ม็อบ18กรกฎา, #7AugMob). This format ensured specificity and prevented overlap between protests occurring within short intervals.

Date-coded hashtags enabled clearer categorization and traceability of each event, reflecting a practical adaptation to Thailand's fast-moving protest cycles. By maintaining unique, concise, and easily recognizable identifiers, participants could organize, archive, and differentiate protest communication more effectively. This practice aligns with general principles of event-based social media logic, facilitating precise mapping between tweets and distinct protest events for subsequent event-contingent analysis. The initial corpus comprised 594,006 tweets. Only original tweets were retained to avoid double-counting engagement. Basic quality assurance included deduplication by tweet ID and manual inspection of sample records to ensure metadata integrity.

3.2.2. Event Window and Contextual Anchoring

To anchor communication temporally and contextually, the analysis was restricted to a 48 h window surrounding each protest—covering the protest day and the following day. Prior work on protest communication cycles shows that engagement typically peaks within 24–48 h (Lotan et al., 2011; Bruns & Hanusch, 2017). A sensitivity analysis using a 24 h window produced comparable visibility distributions, confirming that the 48 h frame effectively captured the dynamic attention span of protest publics.

3.2.3. High-Engagement Sampling

Within each event-specific subset, the 100 tweets with the highest retweet counts were retained; for smaller events, all available tweets were included. This produced a final sample of 1924 tweets across 21 events. The Top-100 absolute cutoff was adopted to maintain a consistent analytic unit across events with varying tweet volumes. This approach, while not representative of all discourse, enables comparison of visibility dynamics without confounding effects from event size. An auxiliary percentile-based check (top 1% per event) yielded similar results, indicating the robustness of the selection strategy. The purpose of this design is not to capture all voices but to examine how high-visibility content embodies algorithmic and affective amplification within Thailand's protest communication ecosystem. Importantly, the analysis does not aim to estimate population-level retweet rates or predict absolute visibility across all tweets. Instead, it examines relative mean differences within a theoretically defined high-visibility subset, asking when and how content and format differentiate visibility among already-amplified messages within each event.

3.2.4. Event Context Annotation

Although the event variable was treated categorically in the statistical analysis, each protest event was qualitatively annotated for contextual characteristics, including crowd size, police presence, and levels of confrontation. These annotations were used as interpretive aids to contextualize patterns observed in the quantitative analysis, rather than as independent explanatory variables.

3.2.5. Interpreting Retweets as Visibility

Retweet counts are treated as a proxy for algorithmic visibility. Prior research demonstrates that engagement metrics shape ranking and reach (Huszár et al., 2022). In this study, retweeting is thus conceptualized as a mechanism through which affective alignment is made algorithmically consequential. The focus on high-engagement tweets captures how collective attention materializes under digital mediation, while recognizing that low-engagement and marginal voices remain under-represented.

3.2.6. Reproducibility

All hashtags, parameters, and filtering steps are documented. Data collection scripts and de-identified tweet IDs are available upon request, consistent with ethical and institutional requirements.

3.3. Thematic Analysis and Coding Procedure

A thematic analysis was conducted to capture the communicative intent and framing of protest-related tweets. Following Braun and Clarke's (2006) six-phase approach, two researchers first familiarized themselves with the data, generated initial codes, and then collaboratively developed a shared codebook. This codebook was refined through iterative cycles of application and discussion until thematic saturation was reached (Lindekilde, 2014). Thematic analysis is widely used in protest communication research because it enables researchers to identify message functions, uncover framing practices, and interpret how participants construct meaning during contentious political events.

Coding proceeded in three stages. In the calibration stage, both coders jointly annotated a pilot subsample to align interpretations of protest-related content. In the main coding stage, the researchers coded tweets independently, meeting periodically to compare decisions and reconcile discrepancies. In the final stage, the entire coded dataset was reviewed to ensure internal consistency and fidelity to the observed data. While some tweets contained elements of multiple themes (for example, both grievance expression and mobilization), coders assigned each tweet to the dominant theme that best reflected its primary communicative intent. This approach aligns with prior studies using functional coding of political communication (Stieglitz & Dang-Xuan, 2013), ensuring mutual exclusivity among thematic categories for subsequent statistical testing.

The resulting coding scheme comprised five overarching themes—information dissemination, grievance expression, mobilization, moral support, and call-outs for action—each with several sub-themes (Table 1). These categories were designed to reflect the functions and frames through which users engaged with protest events, providing a content-based independent variable for the statistical analysis.

Table 1. Themes and Sub-themes of Protest-related Tweets.

Theme	Sub-Theme
Theme 1: Information Dissemination	Protest situations
	Police action
	General movement information
Theme 2: Grievance Expression	Mainstream media
	Police officers
	Government and the Prime Minister
	Monarchy
	Political opponents
Theme 3: Mobilization	Support for gatherings
	Information forwarding
	Boycott of goods/influencers
	Support for goods/influencers
Theme 4: Moral Support	Care for protestors
	Admiration for protestors and supporters
	General protest support
Theme 5: Call-outs for Action	Release of detained individuals
	Calling out influencers for political expression
	Tactical reviews of protest strategies

Intercoder reliability for the full sample (n = 1924) was assessed using Cohen's Kappa. The Kappa coefficient was $\kappa = 0.779$ ($p < 0.001$). Following both Landis and Koch (1977) and Altman (1991), values between 0.61 and 0.80 are interpreted as indicating "substantial" or "good" agreement. Rather than treating this figure as a purely technical benchmark, it was used as part of an iterative process: disagreements were examined, discussed, and resolved by consensus, contributing to the refinement of the codebook.

3.4. Variable Construction

Five variables were constructed for quantitative analysis. One dependent variable and four independent variables were specified. The dependent variable is log-transformed retweet counts (LogRetweet), representing tweet-level visibility. The independent variables are content theme, media presence, time of tweet, and protest event.

3.4.1. Log-Transformed Retweets (LogRetweet)

Retweet count served as an indicator of tweet-level visibility. Because the distribution of retweets was highly skewed, a natural logarithmic transformation was applied. This transformation reduces the influence of extreme values and supports the use of parametric tests, while acknowledging that retweets capture a specific dimension of engagement—circulation—rather than deliberation or commitment.

3.4.2. Content Theme

Each tweet was assigned to one of the five thematic categories produced by the coding procedure. These themes capture differences in communicative intent, such as providing situational information, expressing grievances, mobilizing participation, offering moral support, or calling for specific actions. Although affective tone is central to the conceptual framing of visibility, automated sentiment or emotion analysis was not employed. Existing tools for Thai-language sentiment detection remain limited in accuracy for politicized discourse, often misclassifying sarcasm, irony, or culturally specific expressions (Phatthiyaphaibun et al., 2021). Instead, affective dimensions were captured indirectly through thematic coding—particularly the distinction between grievance, mobilization, and moral support—which reflect emotional orientations embedded in protest communication. It is important to clarify that affect is not measured directly in this study. Retweet counts are treated not as indicators of individual emotional states, but as behavioral traces of affective resonance at the collective level. Amplification is therefore interpreted as observable engagement reflecting alignment between message framing and shared emotional orientations under specific event conditions, rather than as a direct psychological measure of emotion.

3.4.3. Media Presence

Media presence indicates whether a tweet contained at least one image or video (coded 1) or was text-only (coded 0). This variable operationalizes the structural affordance of visual media, which previous research associates with heightened emotional resonance and shareability.

3.4.4. Time of Tweet (ToT)

To capture temporal dynamics relative to protest activity, tweets were coded with reference to the protest day (D0) and the following day (D1). Tweets were grouped into four time bands: early-day (00:00–10:00), daytime protest hours (10:00–18:00), evening (18:00–23:59), and the day after the protest (00:00–23:59). This variable functions as a structural control, allowing the analysis to assess whether event-driven attention overrides ordinary diurnal rhythms in the circulation of highly visible content.

3.4.5. Event

Finally, a categorical event variable distinguished the 21 protest days. This variable represents the broader socio-political context—differences in salience, perceived risk, and symbolic meaning—within which tweets were produced and circulated. In the analysis, it enables examination of whether content and structural features operate similarly across events or are conditioned by event-specific circumstances. To avoid conceptual ambiguity regarding the role of events in the analysis, the event variable requires explicit clarification in relation to other content and structural variables.

In this study, the event is conceptualized as a contextual container rather than a single causal variable, allowing examination of how content themes, media presence, and temporal positioning operate differently within and across protest events.

3.5. Statistical Analysis

To examine how content themes, structural features, and event context were associated with tweet visibility, a univariate analysis of variance (ANOVA) was conducted using Jamovi 2.6.26, an open-source statistical software built on the R platform. The dependent variable was the natural logarithm of retweet counts (LogRetweet). Independent variables comprised content theme, media presence, time of tweet, and event.

A multi-factor ANOVA was selected because the research questions concern differences in mean visibility across groups defined by categorical predictors (events, themes, media presence, and temporal bands). Although the dataset is observational and external conditions are not experimentally controlled, ANOVA remains appropriate when the analytical objective is to compare group means rather than model continuous relationships. Additionally, a multi-factor ANOVA provides a clear framework for testing interaction effects—such as whether the influence of content theme or media presence varies by event context—which aligns with the study's conceptual emphasis on event-contingent visibility dynamics.

As methodologists note, the appropriateness of an analytical technique depends on the nature of the research question rather than on whether data originate from experimental or observational contexts (Keppel & Wickens, 2004). Because the present study focuses on differences in mean retweet visibility across categorical conditions—and on whether these effects interact—analysis of variance provides a suitable and transparent analytical framework. Moreover, the analytical focus is on between-event comparisons and cross-factor interactions (e.g., whether theme or media effects differ by event), rather than decomposing within-event variance. Within this design, selection on the dependent variable is unlikely to bias the specific within-sample comparisons, as the analysis targets conditional differences among already amplified tweets rather than population-level engagement likelihood. Importantly, the aim of the analysis is not to partition variance across hierarchical levels or to model event-level random effects, but to assess whether and how mean visibility differs across categorical conditions and whether these differences are contingent on event context. In this respect, a multi-factor ANOVA is analytically aligned with the study's epistemic focus on comparative patterns and interaction effects, rather than on variance decomposition or individual-level prediction.

Although tweets are nested within protest events, several considerations support the use of ANOVA. Tweets were independently produced by different users at different times, reducing direct dependence within events. Moreover, the analytical focus is on between-event comparison—examining whether mean visibility differs across events and whether the effects of content themes or media formats vary by event context—rather than on decomposing within-event variance. Given the categorical nature of the predictors and the study's emphasis on interaction effects, ANOVA provides an appropriate framework for assessing mean differences and conditional relationships across protest events. While hierarchical models are valuable when within-cluster dependence is substantial, ANOVA remains suitable when clustering effects are limited and the primary objective is comparative.

To deepen the analysis of contextual effects, post hoc tests were conducted to interpret the interaction between event and theme. Tests of between-subjects effects were used to evaluate main and interaction terms. Where statistically significant differences emerged between content themes, post hoc pairwise comparisons with Sidak adjustment were conducted to account for multiple testing. Statistical significance was evaluated at the 0.05 level, and results are interpreted in light of the study's focus on high-visibility tweets rather than the full universe of protest communication.

3.6. Ethical Considerations

The study protocol was approved by the Academic and Ethics Committee of Walailak University (approval number WUEC-22-029-01). All data consisted of publicly available tweets; no direct contact with users took place. In line with AOIR (2020) guidelines on internet research ethics, personally identifiable information—such as usernames, profile names, and precise locations—was removed prior to analysis. Potentially sensitive content is not reproduced verbatim, and findings are reported in aggregate form. Data are stored securely and used solely for academic purposes, with care taken not to further expose or amplify individual users beyond their original online context.

4. Findings

4.1. Overview of the Statistical Analysis

This section reports the results of the statistical analysis, focusing on whether tweet visibility varied systematically across protest events and whether the effects of content theme, media presence, and posting time were conditioned by event context. Interpretation of these patterns is taken up in the Discussion section (Section 5).

A four-way between-subjects analysis of variance was conducted to examine how theme, event, time of tweet (ToT), and media format influenced LogRetweet during Thai protests in 2021 (Table 2). Because the dataset is unbalanced across factor combinations, not all Theme × Event × Time of Tweet × Media cells contain observations. Accordingly, the reported degrees of freedom reflect only estimable components of the model rather than the full factorial design.

Table 2. Four-Way ANOVA Results for Factors Influencing LogRetweet During Thai Protests in 2021.

Source	SS	*df*	MS	*F*	*p*	η^2_p
Theme	1.35	4	0.34	2.08	0.08	0.006
Event	620.81	20	31.04	191.8	<0.001 *	0.72
ToT	0.85	3	0.28	1.76	0.15	0.004
Media	1.2	1	1.2	7.41	0.010 *	0.005
Theme × Event	20.52	75	0.27	1.69	<0.001 *	0.078
Theme × ToT	1.97	12	0.16	1.01	0.43	0.008
Theme × Media	0.46	4	0.11	0.7	0.59	0.002
Event × ToT	7.22	56	0.13	0.8	0.86	0.03
Event × Media	6.97	20	0.35	2.15	0.002 *	0.028
ToT × Media	0.18	3	0.06	0.36	0.78	0.001
Theme × Event × ToT	19.73	107	0.18	1.14	0.16	0.076
Theme × Event × Media	8.86	51	0.17	1.07	0.34	0.035
Theme × ToT × Media	1.72	9	0.19	1.18	0.3	0.007
Event × ToT × Media	5.86	33	0.18	1.1	0.32	0.024
Theme × Event × ToT × Media	4.13	20	0.21	1.28	0.19	0.017
Error	241.3	1491	0.16			

Note. * indicates statistical significance at $p < 0.05$. Data derived from the author's analysis.

4.2. Interaction Effects

The analysis revealed that the four-way interaction of Theme × Event × Time of Tweet × Media was not statistically significant ($F(20, 1491) = 1.28$, $p = 0.19$). Therefore, the three-way interaction effects were examined, and none reached statistical significance:

Theme × Event × Time of Tweet ($F(107, 1491) = 1.14$, $p = 0.16$), Theme × Event × Media ($F(51, 1491) = 1.07$, $p = 0.34$), Theme × Time of Tweet × Media ($F(9, 1491) = 1.18$, $p = 0.30$), and Event × Time of Tweet × Media ($F(33, 1491) = 1.10$, $p = 0.32$).

Examination of the two-way interaction effects showed that the Theme × Event was significant, $F(75, 1491) = 1.69$, $p < 0.001$, indicating that the impact of thematic content on retweet counts varied across different protest events, and Event × Media was significant, $F(20, 1491) = 2.15$, $p = 0.002$, suggesting that the effectiveness of Media in the tweets in generating retweets depended on the specific protest event.

No other two-way interactions reached statistical significance: Theme × Time of Tweet ($F(12, 1491) = 1.01$, $p = 0.43$), Theme × Media ($F(4, 1491) = 0.70$, $p = 0.59$), Event × Time of Tweet ($F(56, 1491) = 0.80$, $p = 0.86$), and Time of Tweet × Media ($F(3, 1491) = 0.36$, $p = 0.78$).

Time of Tweet was not involved in any significant interaction, and its main effect was not significant, $F(3, 1491) = 1.76$, $p = 0.15$, indicating that it was not a factor in retweet engagement.

These findings indicate that during the 2021 Thai protests, retweet engagement depended upon the specific protest event and the media format used in tweets, and upon the specific protest event and the thematic content of tweets, suggesting that media effectiveness and message framing effectiveness was context-dependent. The non-significant effect of time of tweet suggests that temporal factors had less influence on retweet patterns during these protests compared to content and presentation factors.

4.3. Event-Contingent Theme Effects

The significant interaction effect of Theme × Event suggests that the effect of Themes (Information, Grievance, Mobilization, Support, Call-out) on retweet counts during Thai protests in 2021 depends upon the particular Event. The analysis of simple main effects revealed that thematic content had a statistically significant effect on sharing behavior in only 6 out of the 21 political events analyzed.

The significant simple main effects of Theme on LogRetweet for Event 307 ($F(4, 1491) = 5.89$, $p < 0.001$), Event 313 ($F(4, 1491) = 5.85$, $p < 0.001$), Event 404 ($F(4, 1491) = 3.52$, $p = 0.007$), Event 410 ($F(4, 1491) = 3.41$, $p = 0.009$), Event 429 ($F(4, 1491) = 4.99$, $p = 0.001$), and Event 1114 ($F(4, 1491) = 2.60$, $p = 0.035$) are shown in Table 3.

Table 3. Simple Main Effects of Theme on LogRetweet for Six Events.

Event	Sum of Squares	*df*	Mean Square	*F*	*p*
307	3.82	4	0.95	5.89	<0.001
313	3.78	4	0.95	5.85	<0.001
404	2.28	4	0.57	3.52	0.007
410	2.21	4	0.55	3.41	0.009
429	3.23	4	0.81	4.99	0.001
1114	1.68	4	0.42	2.60	0.035

Note. Each *F* test examines the simple effects of Theme within Event. Data derived from the author's analysis.

For the remaining 15 political events, Theme did not significantly influence retweet counts. These findings suggest that the relationship between message theme and retweet behavior during political movements is context-specific, with only certain events demonstrating sensitivity to message framing strategies.

Following the identification of significant simple main effects of the Theme on LogRetweet in six political events, pairwise comparisons were conducted to determine which specific themes generated higher retweet rates within each event (see Table 4 and Figure 1).

Table 4. Significant Differences in Mean LogRetweet Across Themes for Six Events.

Event	Comparison Pairs	Mean Difference	*p*
307 (Mob 7 March 2021)	Information < Mobilization	−0.651	<0.001
313 (Mob 13 March 2021)	Information < Call-out	−1.263	<0.001
	Grievance < Call-out	−0.978	0.007
	Mobilization < Call-out	−1.135	0.001
	Support < Call-out	−1.118	0.001
404 (Mob 4 April 2021)	Information < Support	−0.758	0.008
	Grievance < Support	−0.621	0.033
	Support > Call-out	0.893	0.015
410 (Mob 10 April 2021)	Information < Mobilization	−0.499	0.042
	Grievance < Support	−0.508	0.042
429 (Mob 29 April 2021)	Information > Grievance	0.402	0.014
	Information > Mobilization	0.543	0.007
	Grievance < Call-out	−0.417	0.042
1114 (Mob 14 November 2021)	Information > Mobilization	0.307	0.043
	Grievance > Mobilization	0.446	0.016

Note. Data derived from the author's analysis.

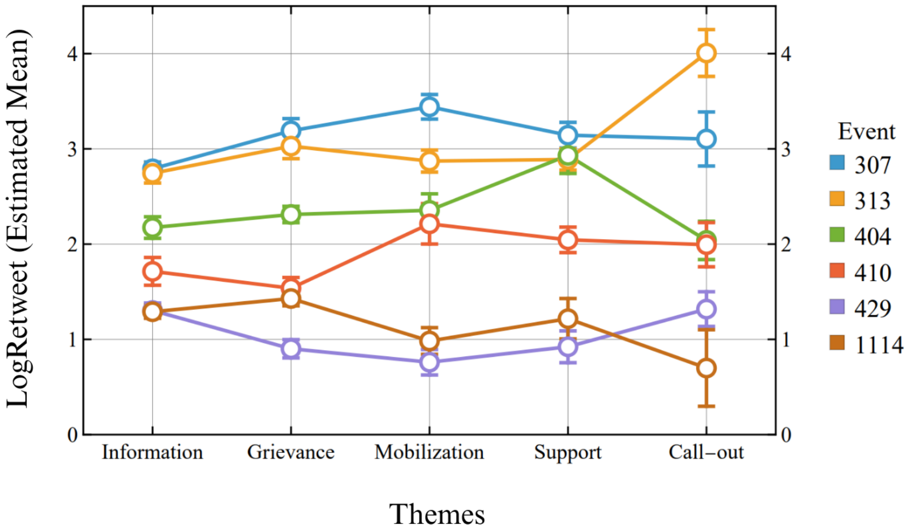

Figure 1. Comparison of Estimated Mean LogRetweet Values Across Different themes for Different Events. (Error bar ± 1SE). *Note.* Data derived from the author's analysis.

In Event 307, the Information theme received significantly fewer retweets than the Mobilization theme (*M*diff = −0.651, $p < 0.001$); otherwise there were no significant differences.

Event 313 showed the Call-out theme as the most prominent, receiving significantly more retweets than the other themes of Information (*M*diff = −1.263, $p < 0.001$), Grievance (*M*diff = −0.978, $p = 0.007$), Mobilization (*M*diff = −1.135, $p = 0.001$), and Support (*M*diff = −1.118, $p = 0.001$). Otherwise, there were no significant differences.

The Support theme emerged as popular in Event 404, receiving more retweets than Information (*M*diff = −0.758, $p = 0.008$), Grievance (*M*diff = −0.621, $p = 0.033$), and Call-out (*M*diff = 0.893, $p = 0.015$). Otherwise, there were no significant differences.

In Event 410, the Information theme received fewer retweets than Mobilization (Mdiff = −0.499, p = 0.042), while Grievance received fewer retweets than Support (Mdiff = −0.508, p = 0.042). Otherwise, there were no significant differences.

By contrast in Event 429, the Information theme received more retweets than both Grievance (Mdiff = 0.402, p = 0.014) and Mobilization (Mdiff = 0.543, p = 0.007), while Grievance received fewer retweets than Call-out (Mdiff = −0.417, p = 0.042). Otherwise, there were no significant differences.

In Event 1114, both Information (Mdiff = 0.307, p = 0.043) and Grievance (Mdiff = 0.446, p = 0.016) received more retweets than Mobilization theme. Otherwise, there were no significant differences.

For the six events where mean LogRetweet between Themes was significantly different, there was no particular pattern according to which one Theme was significantly more retweeted than another.

The significant interaction effect of Theme × Event suggests that differences in the count of retweets for each of the content theme (Information, Grievance, Mobilization, Support, Call-out) were dependent upon the particular event.

As shown in Table 5, there were highly significant differences between Events on LogRetweet for each of the five Themes.

Table 5. Simple Main Effects of Event on LogRetweet for Each Theme.

Theme	Sum of Squares	*df*	Mean Square	*F*	*p*
Information	421.82	20	21.09	130.32	<0.001
Grievance	506.99	20	25.35	156.64	<0.001
Mobilization	232.71	20	11.64	71.90	<0.001
Support	139.15	20	6.96	42.99	<0.001
Call-out	65.64	15	4.38	27.04	<0.001

Note. Data derived from the author's analysis. The Call-out theme was not observed in all protest events; therefore, the event-level analysis for this theme includes fewer events, resulting in a reduced event degrees of freedom (df = 15).

Post hoc pairwise comparisons were conducted to identify specific differences between events within each theme. There were no consistent patterns indicating which Events differed for which Themes. For instance, in event 328:

- Within the Information theme, its mean retweet count was significantly lower than that of 9 other events, and higher than that of 4 events.
- Within the Grievance theme, it was significantly lower than that of 4 events, and higher than that of 9 events.
- Within the Mobilization theme, it was lower than that of 9 events, and higher than that of 3 events.
- Within the Support theme, it was lower than that of 12 events, and higher than that of 4 events.
- Within the Call-out theme, it was lower than that of 2 events, and higher than that of 2 events.

While some events with higher retweet counts appeared in more than one theme, there was no single event or group of events that consistently ranked highest or lowest across all themes.

The analysis of simple main effects revealed that only two events—Event 429 and Event 1114—demonstrated statistically significant effects of Media on LogRetweet. Table 6 presents the summary of these significant tests.

Table 6. Simple Main Effects of Media on LogRetweet for Two Events.

Event	Sum of Squares	*df*	Mean Square	*F*	*p*
429 (29 April 2021)	7.54	1	7.54	46.59	<0.001
1114 (14 November 2021)	4.79	1	4.79	29.57	<0.001

Note. Data derived from the author's analysis.

4.4. Event-Contingent Media Effects

Specifically, tweets without media attachments demonstrated significantly lower LogRetweet compared to tweets containing media during these two events (Event 429: $F(1, 1491) = 46.59$, $p < 0.001$; Event 1114: $F(1, 1491) = 29.57$, $p < 0.001$).

This media effect was not observed for any of the other 19 political events analyzed in the dataset. These findings suggest that the influence of media attachments on information diffusion varies substantially depending on the specific event, with certain events demonstrating a particularly strong dependence on visual or multimedia content for broader dissemination through retweets.

Post hoc pairwise comparisons were conducted to identify specific differences between tweets with media and tweets without media for the events showing significant effects. The results indicated that for Event 429 (29 April 2021), tweets without media had significantly lower LogRetweet values than tweets with media (Mdiff = −0.742, $p < 0.001$). Similarly, for Event 1114 (14 November 2021), tweets without media showed significantly lower LogRetweet values compared to tweets with media (Mdiff = −0.595, $p < 0.001$), as shown in Table 7 and Figure 2.

Table 7. Pairwise Comparisons of LogRetweet Values Between Media Conditions for Two Events.

Event	Comparison Pairs	Mean Difference	*p*
429 (29 April 2021)	without media < with media	−0.742	<0.001
1114 (14 November 2021)	without media < with media	−0.595	<0.001

Note. Data derived from the author's analysis.

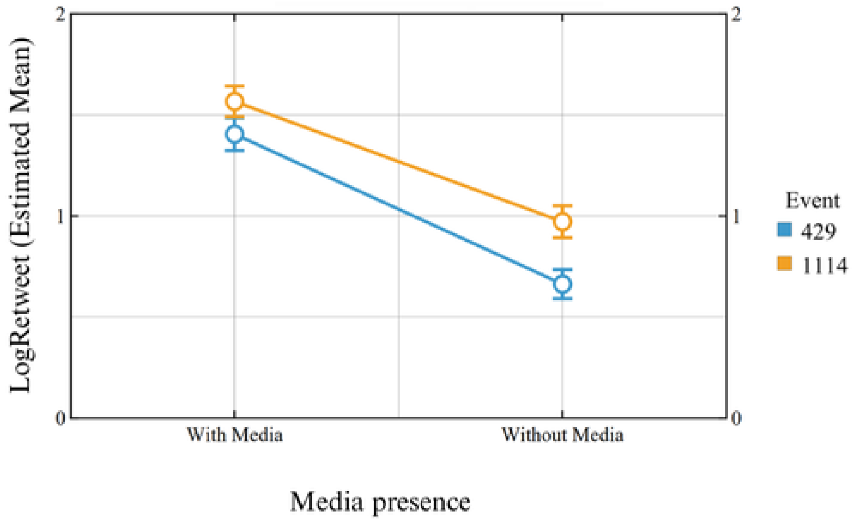

Figure 2. Comparison of Estimated Mean LogRetweet Across Tweets With and Without Media For Different Events. (Error bar ± 1SE). *Note.* Data derived from the author's analysis.

These findings demonstrate that for these specific political events, the inclusion of media in tweets was associated with substantially higher rates of information diffusion through retweets.

Results revealed significant simple main effects of Event on LogRetweet both for tweets without media ($F(20, 1491) = 172.09$, $p < 0.001$) and for tweets with media ($F(20, 1491) = 189.82$, $p < 0.001$). These findings indicate that the Event factor significantly influenced retweet numbers for both media conditions, as shown in Table 8.

Table 8. Univariate Tests of Event Effects on LogRetweet by Media Presence.

Media	Sum of Squares	*df*	Mean Square	*F*	*p*
without media	557	20	27.85	172.09	<0.001
with media	614.4	20	30.72	189.82	<0.001

Note. Data derived from the author's analysis.

Pairwise comparisons revealed significant differences between specific events for tweets without media content, as well as between specific events for tweets with media content. In general, differences between events were broadly in line with differences in retweet counts.

5. Discussion

5.1. Event Context and Event-Centered Visibility

The strong explanatory role of event context highlights the relevance of event-centered approaches in the study of digital protest (Sewell, 1996; McAdam & Snow, 2010). In this study, protest events are treated as contextual containers rather than isolated variables. Each event bundles together multiple situational dimensions—including perceived political risk, emotional intensity, symbolic meaning, and media attention—that jointly shape how protest communication circulates.

Across the dataset, events varied in their dominant characteristics, ranging from confrontational episodes involving state repression to more symbolic or commemorative gatherings. These differences produced distinct conditions for visibility. Without discrete protest events, differences in content or media form mattered relatively little; during politically salient events, however, these same differences became consequential as attention, affect, and amplification converged. This finding underscores the limitations of aggregating protest communication across extended periods, as such approaches risk obscuring the event-specific dynamics that structure collective attention.

Empirically, this pattern is reflected in the statistical results showing that thematic content significantly influenced retweet visibility in only 6 out of the 21 protest events analysed. For example, during Event 307 (7 March 2021), mobilization-themed tweets received significantly higher mean retweet counts than information-oriented tweets ($p < 0.001$), whereas in Event 313 (13 March 2021), call-out messages were amplified more strongly than all other thematic categories ($p < 0.001$). In contrast, for the remaining 15 events, thematic differences did not produce statistically significant variation in visibility.

Similarly, visual media enhanced retweet visibility only during a small subset of events. Media presence significantly increased mean retweet counts in Event 429 (29 April 2021) and Event 1114 (14 November 2021), but had no measurable effect in the majority of protest events. These results demonstrate that visibility advantages associated with content framing or media format emerge only under specific event conditions, rather than operating uniformly across time.

Together, these findings illustrate how event context structures the conditions under which amplification becomes possible, reinforcing the need to conceptualize visibility as an event-contingent process rather than a stable property of messages or platforms.

5.2. Event-Contingent Connective Action

These findings refine theories of connective action by foregrounding temporality and context as organizing principles (Bennett & Segerberg, 2012). While connective action theory emphasizes digitally mediated, personalized participation, it often assumes continuity of engagement. The present findings empirically illustrate the discontinuous, event-bound nature of visible connective engagement.

Retweeting is conceptualized here as a minimal connective act: a low-cost signal of alignment that contributes to amplification, rather than a comprehensive indicator of networked coordination or sustained mobilization. By examining differences in mean retweet visibility across events and their interactions with content and media features, the analysis clarifies when connective action becomes publicly visible and when it recedes.

Empirically, this episodic pattern is evident in the fact that thematic effects on visibility emerged in only a small subset of protest events, while remaining absent in the majority of cases. For example, grievance- or call-out–oriented tweets achieved significantly higher visibility during a limited number of high-salience, confrontational protests, whereas the same themes showed no amplification advantage during routine or symbolic events.

This concentration of visible engagement within specific political moments indicates that connective action does not accumulate gradually or persist uniformly over time. Instead, it materializes in short bursts when event salience, emotional resonance, and perceived political risk converge, creating temporary windows in which retweeting becomes a meaningful form of public alignment. Connective action, in this account, is episodic rather than continuous, emerging most clearly during moments of heightened political salience.

5.3. Context-Sensitive Affective Publics

The findings also extend the framework of affective publics by illustrating how affective alignment operates under conditions of political constraint (Papacharissi, 2015). Rather than measuring affect directly, this study infers affective dynamics from observable patterns of amplification, consistent with research showing that emotionally resonant communication is more likely to circulate widely on social media. Retweets are therefore treated as behavioural traces of affective resonance at the collective level, rather than as direct indicators of individual emotional states.

The significant interaction between event context and content theme indicates that affective resonance was uneven across protest events. The analysis revealed that thematic content significantly shaped retweet visibility in only six of the twenty-one protest events examined, indicating that affective alignment crystallized selectively in response to situational conditions rather than operating uniformly across time. In several high-salience events, particular themes achieved significantly higher visibility than others, while in the majority of events thematic differences had no measurable effect on amplification.

For example, during Event 313 (Mob 13 March 2021), call-out tweets received significantly higher retweet counts than information, grievance, mobilization, and support themes, suggesting that affectively charged appeals demanding accountability resonated strongly in that specific political moment. By contrast, during Event 404 (Mob 4 April 2021), support-oriented tweets achieved higher visibility than grievance- or information-focused messages, indicating a shift toward affective expressions of solidarity under different situational conditions. Similarly, in Event 429 (Mob 29 April 2021), information-oriented tweets were more widely retweeted than grievance and mobilization messages, illustrating that affective resonance does not map consistently onto a single emotional register across events.

These patterns suggest that affect does not generate visibility on its own. Rather, during salient events it lowers the threshold for amplification, making retweeting more likely when emotional orientation, political risk, and event salience align. Affective publics are therefore treated here not as stable or empirically bounded social groups, but as contingent formations that emerge episodically when shared emotional orientations become collectively actionable through platform-mediated visibility. This event-sensitive perspective highlights how affective alignment is structured by political context and platform affordances, rather than operating as a continuous or uniform driver of engagement.

5.4. Visual Media, Algorithmic Amplification, and Negotiated Visibility

Consistent with scholarship on platform visibility and visual witnessing, tweets containing images or videos achieved higher mean retweet counts overall, although the main effect of media was small and strongly conditioned by event context. However, the significant interaction between event context and media presence shows that visuality did not confer a uniform advantage. Instead, visual media enhanced visibility only during specific protest events.

This conditional effect is evident in Events 429 (29 April 2021) and 1114 (14 November 2021), where tweets containing images or videos received significantly higher mean LogRetweet values than text-only tweets. In contrast, no statistically significant media effect was observed in the remaining 19 protest events. These findings indicate that visual media amplified engagement primarily during moments of heightened political salience, rather than functioning as a general driver of visibility across all protest contexts.

In Thailand's semi-authoritarian context, visual communication often entails heightened political risk. Images documenting protest activity or symbolic defiance may invite surveillance or legal repercussions, encouraging users to adopt visually expressive yet strategically ambiguous forms of communication. Visibility should therefore be understood as a negotiated outcome, shaped by the alignment of affective resonance, perceived safety, and algorithmic prioritization. Retweet visibility reflects not viral popularity alone, but context-dependent judgments about when amplification is meaningful and acceptable.

The fact that media effects emerged only in specific events suggests that users collectively calibrated their willingness to amplify visual content in response to perceived risk and urgency. Visuality became most consequential when it aligned with moments of confrontation, symbolic escalation, or intensified public attention—conditions under which witnessing outweighed concerns about exposure.

More broadly, recent shifts in Twitter's platform governance and algorithmic moderation—particularly following its acquisition by Elon Musk—underscore the instability of visibility regimes on the platform. Changes in content moderation practices, verification systems, and algorithmic ranking may further intensify the volatility of protest visibility, reinforcing the need to treat amplification as historically contingent rather than platform-invariant.

5.5. High-Visibility Discourse and Analytical Scope

By design, this study focuses on high-visibility protest discourse rather than the full ecology of participation on Twitter. Prior research has shown that platform visibility is highly unequal, with a small subset of posts capturing disproportionate attention. Visibility itself thus constitutes a form of symbolic power, particularly in contexts where access to mainstream media is constrained.

At the same time, visibility should not be conflated with representativeness. The findings illuminate how amplification operates during discrete protest events, but they do not capture low-visibility forms of participation or dissent. The results should therefore be read as an analysis of visible protest communication under specific political conditions, rather than as a comprehensive account of all protest activity on the platform.

5.6. Implications for the Study of Digital Protest

Taken together, the findings point to three implications for the study of digital protest communication. First, event context plays a central role in organizing visibility, shaping when and how engagement becomes amplified. Second, connective action operates as an episodic rather than continuous process, becoming publicly visible primarily during moments of heightened salience. Third, affective amplification is context-sensitive, conditioned by political risk, platform governance, and event-specific dynamics.

By conceptualizing visibility as an event-contingent process rather than a stable attribute of messages or users, this study contributes to a more contextually grounded understanding of digital activism. The Thai case illustrates how publics negotiate attention, emotion, and risk within constrained media environments, underscoring the importance of event-sensitive approaches for analyzing digital protest under conditions of repression and volatility.

5.7. Contextualizing Western Theoretical Frameworks

A central contribution of this study lies in illustrating how theoretical frameworks developed primarily within Western democratic contexts operate when applied to semi-authoritarian settings. Much of the scholarship on digital activism—including connective action theory (Bennett & Segerberg, 2012) and affective publics (Papacharissi, 2015)—has been grounded in protest movements emerging from relatively open media environments, where legal risks associated with online expression are comparatively limited. As a result, these frameworks have tended to foreground platform affordances, personalization, and affective resonance, while paying less explicit attention to how political repression, surveillance, and legal sanctions may condition communicative practices.

Findings from the Thai case suggest that visibility in protest communication cannot be understood solely as a function of algorithmic amplification or emotional intensity. Instead, visibility emerges as a negotiated outcome shaped by political risk. Protest participants in Thailand operate within a legal and institutional environment that includes lèse-majesté provisions, emergency decrees, and the possibility of prosecution for certain forms of expression. These conditions influence not only what participants choose to say, but also how, when, and whether content is collectively amplified.

The event-contingent pattern observed in this study—where content themes and media formats became consequential only during moments of heightened political salience—indicates that engagement is calibrated in response to shifting perceptions of opportunity, threat, and collective safety. Such dynamics complicate assumptions, often implicit in Western-centric accounts, that visibility primarily reflects stable preferences or continuous participation.

By foregrounding these contextual constraints, this study positions the Thai protest case not merely as an application of existing theories, but as a site for theoretical refinement. It demonstrates how connective action and affective dynamics are reconfigured under conditions where political expression carries material risk, thereby contributing to broader efforts to develop more context-sensitive and globally inclusive theories of digital protest.

6. Conclusions

This study set out to examine how visibility in digital protest communication is shaped by the interaction of event context, content characteristics, media formats, and timing within a semi-authoritarian media environment. Drawing on a high-visibility corpus of protest-related tweets from Thailand, the findings demonstrate that engagement on Twitter is not distributed evenly across time or message features. Instead, visibility emerges as a contingent, event-driven process structured by political salience, affective intensity, and platform affordances.

Across the 21 protest events analyzed, event context accounted for the largest share of variation in retweet visibility. This pattern suggests that discrete political moments play a central role in organizing collective attention, shaping when amplification becomes more likely and when it recedes. Content themes and media formats mattered, but their effects were conditional rather than uniform, varying across events with different emotional and political characteristics. These findings underscore the importance of treating protest events not merely as background variables, but as contextual configurations that shape how communication circulates and gains prominence.

By foregrounding temporality and context, this study refines existing accounts of connective action and affective publics. Rather than assuming continuous participation or stable engagement patterns, the analysis highlights the episodic nature of visible connective action, which becomes publicly legible primarily during moments of heightened political salience. Affective publics, in this account, are not treated as fixed or bounded collectives, but as analytically useful lenses for interpreting how emotional resonance and amplification align under specific event conditions.

Methodologically, the study demonstrates the conceptual value of high-visibility sampling for analyzing protest communication. Focusing on highly amplified tweets allows for closer examination of the forms of expression and signals that publics elevate most strongly during critical moments. At the same time, such an approach does not capture the full ecology of participation on the platform. Low-visibility forms of engagement, silent observation, and non-amplified dissent remain outside the scope of this analysis. Visibility should therefore not be conflated with representativeness, but understood as a specific dimension of political communication shaped by unequal attention and algorithmic prioritization.

Several limitations should be acknowledged. The analysis relies on retweet counts as an indicator of visibility, which does not capture users' motivations, interpretations, or offline forms of participation. Nor does the study measure affect directly; affective dynamics are inferred from patterns of amplification rather than from sentiment analysis or qualitative user data. In addition, the focus on a single platform and a specific national context limits the generalizability of the findings. Moreover, ongoing changes to Twitter's governance, algorithms, and content moderation practices—particularly following its acquisition by Elon Musk—may alter visibility dynamics in ways that are not captured by data from earlier periods. The rollback of content moderation, changes to verification systems, and shifts in algorithmic prioritization under Musk's ownership raise critical questions about the platform's reliability as an infrastructure for protest communication, particularly in contexts where digital repression is already prevalent. This instability complicates earlier claims about Twitter's role in enabling transnational solidarity, as the platform's governance now appears increasingly volatile and less responsive to the needs of activists operating under authoritarian constraints. These limitations, however, are consistent with the study's analytical aims and point to productive directions for future research.

Future studies could extend this event-centered approach by comparing visibility dynamics across platforms with different affordances, such as Facebook or TikTok, or by examining how similar protest events unfold in other political contexts. Combining visibility-focused analyses with qualitative methods or network-based approaches could further illuminate how publics interpret, negotiate, and act upon politically salient events under conditions of constraint.

Taken together, this study contributes to a more context-sensitive understanding of digital protest communication. By conceptualizing visibility as an event-contingent process rather than a stable attribute of messages or users, it highlights how political moments, affective alignment, and platform infrastructures jointly shape what becomes publicly seen and amplified. In doing so, the study underscores the importance of event-sensitive and contextually grounded approaches for analyzing digital activism in environments characterized by repression, volatility, and uneven media freedom.

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