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# How Long Does Agenda Setting Take? A Temporal Analysis of Media-Public Agenda Dynamics During Crisis Events Based on ARIMA Modeling

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**ABSTRACT**

The decentralized digital media landscape has diversified agenda-setting actors, creating challenges like misinformation and emotional amplification that complicate crisis communication. This study investigates the temporal dynamics of traditional media, social media, and public agendas during crisis events, using the Cathay Pacific incident as a representative case of transnational media discourse. Drawing on agenda-setting theory and the public opinion lifecycle model, it applies ARIMA time-series modeling, social network analysis, and Granger causality testing to analyze interactions and lag structures among communication actors across different stages of crisis evolution. Empirically, the study identifies a distinct 40-hour lag between the peak agenda-setting effectiveness of social and traditional media during the early phase of public opinion formation. Social media demonstrated the highest temporal responsiveness within the first 24 hours, with its influence declining after the sixth day, whereas traditional media exhibited delayed but sustained impact on the agenda. These findings reveal that agenda-setting operates through recursive, time-sensitive influence cycles rather than linear dissemination. By integrating theoretical refinement and practical relevance, this study advances temporal agenda-setting research through the quantification of cross-platform lag interactions and the modeling of bidirectional media–public dynamics. The findings further inform crisis communication management, underscoring the need for synchronized cross-platform timing and proactive interventions to preempt misinformation and foster rational public discourse.



## INTRODUCTION

As the media ecosystem grows increasingly complex—with lowered barriers to participation and the rapid proliferation of digital content creation tools—agenda-setting actors shaping the agenda have become more diverse. This diversification introduces new challenges, including misinformation, irrational discourse, and insufficient regulation in the networked public sphere (Guo & Yang, 2023). During crises, the public often struggles to assess the reliability of information and turns to rapidly evolving social media platforms that amplify emotional volatility and contagion. This decentralized flow of information fosters reverse agenda-setting, where audience attention reshapes media priorities, complicating both information governance and crisis communication management (Weimann & Brosius, 2017; Mo et al., 2023).

Currently, social media exerts considerable agenda-setting power in shaping public cognition. Exposure to social media news can significantly influence users' perceptions of issue salience and the perceived relevance of news content (Riezebos et al., 2011). Subsequent studies further corroborated these findings, showing that information circulating on social platforms can rapidly reshape collective understandings of ongoing public debates (Salman et al., 2016; Feezell,

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2018). Notably, as social media ecosystems evolve, the agenda-setting power of media outlets produces shifting patterns of influence and communicative effectiveness (Zhao & Zhang, 2023). However, although the magnitude of this influence is well established, its temporal evolution and lagged dynamics remain insufficiently explored. Understanding these temporal processes is essential for revealing not only how social media shape the public agenda but also when their influence peaks and wanes across different stages of a crisis.

Empirical evidence indicates an apparent acceleration of agenda-setting cycles in the digital era. Cross-media agenda-setting lags have shortened to just one day during election periods (Vonbun, et al., 2016). Delays that once spanned several weeks in traditional media have been compressed to between one and seven days online (Roberts et al., 2002). Reciprocal, issue-dependent interactions between Twitter activity and news coverage occur within zero to seven days (Conway & Kenski, 2015). In contrast, salience shifts can occur in as little as six hours (Wang & Yu, 2020). Collectively, these studies demonstrate that agenda-setting now unfolds through increasingly compressed temporal rhythms, underscoring the need for time-sensitive analytical frameworks to capture these dynamics and explain the reciprocal nature of media–public influence.

The convergence of rapid digitalization and recurring crises has transformed both the media landscape and the public opinion ecology. These dynamics underscore the necessity of examining the temporal dimension of agenda-setting as a core component of crisis communication. Time is not merely a contextual factor but a structural determinant that shapes how agenda relationships emerge, evolve, and decay over time (Neuman et al., 2014). Algorithmic curation and automated information flow further intensify these temporal dynamics, altering agenda-setting processes in social media environments (Karpf, 2012). Such dynamics require analytical approaches that can model temporal dependencies and feedback effects. Time-series methods, particularly the ARIMA model, enable researchers to trace the evolution of agendas and forecast future trends with greater precision (Box et al., 2015; Yang & Saffer, 2019). By integrating computational modeling with agenda-setting theory, it becomes possible to quantify when media–public interactions occur, how long influence persists, and which actors lead or lag at different stages of a crisis.

Digital footprints such as news articles, social media posts, and user interactions offer a rich empirical foundation for examining communication behaviors and their temporal evolution. Advances in computational analytics have expanded the scope of communication research beyond simple correlations to multivariate causal inference, providing robust tools for mapping the dynamic interdependencies within media systems (Granger, 1969; Neuman et al., 2014). The integration of time-series and causal analysis provides a rigorous framework for understanding how agenda-setting mechanisms evolve within the new media ecosystem, capturing how digital technologies continually redirect public attention toward emerging issues and actors.

In China, domestic scholarship on online public opinion has primarily focused on the media's functions (Xie & Rong, 2011), governance mechanisms (Zhang & Yan, 2018), and crisis management strategies (Xiao & Zeng, 2017). These studies highlight fragmented coordination among governance entities and advocate for institutional reforms to enhance the effectiveness of public opinion guidance (Ding, 2023). Meanwhile, international research has examined agenda-setting in diverse contexts such as policy communication (Blinder, 2015), public health (Albalawi & Sixsmith, 2015), and social governance (Breuer & Spring, 2020), revealing that government positions and media framing significantly shape public attitudes.

Despite these valuable insights, existing research often overlooks the inherent dynamism of online discourse, particularly the temporal differentiation of public sentiment and issue salience across the distinct stages of crisis events. To address this gap, agenda-setting research should be contextualized within situational dynamics, employing a temporal–relational perspective to uncover how media and public agendas evolve and interact over time. Accordingly, this study applies agenda-setting theory and the public opinion lifecycle model to analyze the temporal and causal dynamics among traditional media, social media, and the public during crisis events. The following questions guide the research: (1) What are the temporal relationships among conventional media, social media, and the public in the agenda-setting process during different stages of crisis events in China? (2) How do these actors differ in their temporal agenda-setting characteristics across the life cycle of crisis discussions? (3) What trends emerge when forecasting public opinion trajectories, and how do forward and reverse agenda-setting mechanisms interact over time? And (4) What practical insights can the temporal relationships among media and public agendas offer for improving public opinion guidance and crisis communication management?

Moreover, unlike previous agenda-setting studies that primarily emphasized content salience or cross-sectional associations, this research introduces a time-based analytical approach that quantifies agenda-setting lags and bidirectional causal flows between media and public attention. By integrating ARIMA time-series modeling, social network analysis (SNA), and Granger causality testing, the study captures the temporal dependencies and feedback loops that structure crisis communication processes across different stages. Theoretically, this work refines temporal agenda-setting frameworks by conceptualizing time as a structural dimension of influence, thereby extending classical models into a dynamic, data-driven context. Methodologically, it demonstrates the utility of combining ARIMA modeling with network-based measures to uncover nonlinear and reciprocal intermedia dynamics more precisely than static or correlation-based designs. Practically,

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the findings provide actionable implications for crisis communication governance, identifying critical lag windows that inform when coordinated interventions and cross-platform agenda synchronization are most effective.

## METHOD

This study draws on the Cathay Pacific incident as a case study, as it is deeply embedded within historical and political contexts that make it a compelling lens for examining public opinion dynamics. This case is critical for study for three key reasons. First, the complexity of the issue: the incident extends beyond a mere service mishap, reflecting broader concerns about inequality and systemic biases that non-native speakers often face in international and multicultural environments. Second, the rapid spread and influence: the event garnered widespread attention and spread rapidly across social media platforms, offering a valuable opportunity to analyze how public opinion evolves, how narratives are constructed, and how organizations respond in real-time. Third, the event's controversial nature: the circulation of misleading information, the politicization of the issue, and the absence of a clear regulatory framework collectively fueled intense public debate and contributed to a fragmented and chaotic discourse.

This study applies Steven Fink's crisis life cycle to the public opinion surrounding the Cathay Pacific Airways incident, segmenting the communication process into the four phases: latency, outbreak, diffusion, and recovery (Fink, 1986). These stages provide a structured framework for analyzing the evolution of public opinion in response to a crisis. The first stage, public opinion latency, occurs when warning signs of a potential crisis begin to surface but remain largely unnoticed or ignored by the public and the organization. The outbreak stage follows when the issue escalates into a visible problem, drawing public and media attention. During the diffusion stage, the crisis spreads rapidly, intensifying public scrutiny and often damaging the organization's reputation as information circulates widely. Finally, the recovery stage marks the organization's efforts to restore stability, rebuild trust, and learn from the event to prevent future crises.

The analysis focuses on the full life cycle of public opinion surrounding the Cathay Pacific incident, with data collected from May 21 to May 31, 2023, across traditional and social media platforms. Traditional media data were obtained from the Wise News Database. This widely recognized academic source provides daily updates from national and regional outlets, including Global Times, China News Service, Caixin Weekly, Nanfang Daily, and Metropolis Times. For social media, data were gathered from Sina Weibo, focusing on posts from "media"-verified accounts representing credible information sources, while "celebrity"-verified accounts were excluded to ensure reliability. Posts containing the keywords "Cathay Pacific Airways" and "blanket" were collected using the Goo Seeker web crawler, encompassing original posts, reposts, and user comments. To eliminate noise, all datasets underwent a rigorous cleaning process to remove duplicates, irrelevant entries, and invalid content. The final dataset comprised 12,498 Weibo posts, 10,027 user comments, and 139 traditional media reports, providing a comprehensive corpus for analyzing the temporal interaction between traditional media, social media, and the public agenda.

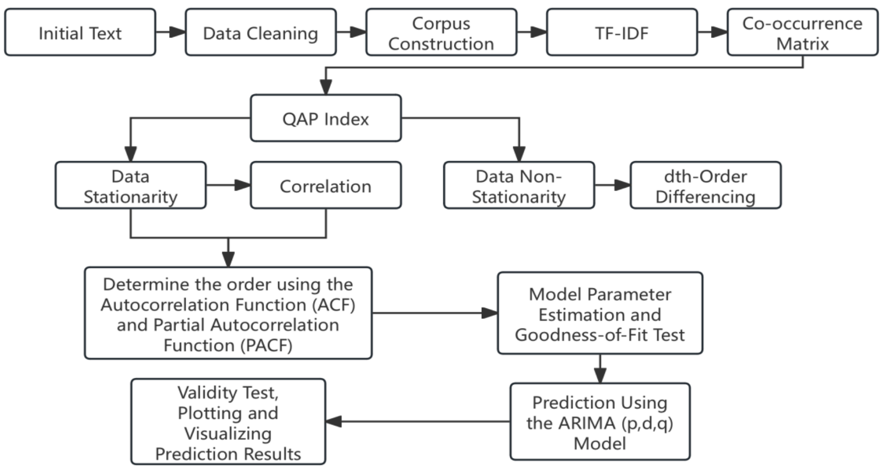


**Figure 1.** Time-Series Agenda Data Analysis and Prediction Framework
Source: Researcher (2025)

As illustrated in Figure 1, the analytical workflow comprises five stages: text preprocessing, co-occurrence mapping, QAP correlation modeling, ARIMA-based forecasting, and model validation, forming a comprehensive computational framework for analyzing and predicting temporal agenda-setting dynamics.

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**FINDING AND DISCUSSION**

The analysis focuses on the full life cycle of public opinion surrounding the Cathay Pacific incident, with data collected from news reports over 11 days (May 21, 2023, to May 31, 2023). Based on Fink's model and the public opinion life cycle theory (Zhang, 2019), the development of public opinion was divided into four stages: the latent period, outbreak period, diffusion period, and pacification period. These stages were further refined based on key milestones, as shown in Figure 2.

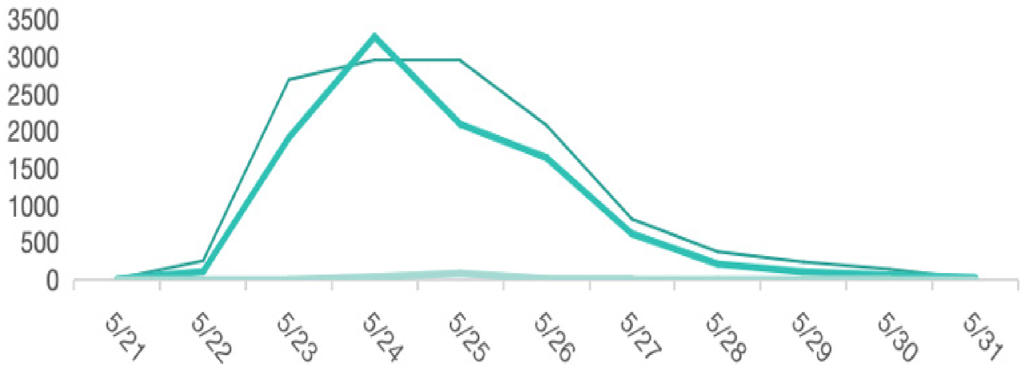


**Fig. 2.** Trend Chart of Hot Topics in the Cathay Pacific Blanket Incident
Source: Goo Seeker (2025)

Based on Figure 2, the analysis of the public opinion lifecycle for the Cathay Pacific Blanket Incident, the crisis can be divided into the following distinct phases: **(1) Latent Period (May 21 - May 22)**: The incident occurred on May 21 and was publicly revealed by the affected party on May 22 through a recording and real-name report. The crisis had not yet fully materialized. During this phase, factors contributing to the crisis steadily accumulated, but the situation had not yet escalated into widespread public concern. **(2) Outbreak Period (May 23 - May 24)**: The crisis gained momentum rapidly during this period, with media involvement through interviews and reports. Public attention surged, and online discussions intensified, marking the escalation of the issue into a full-blown public opinion crisis. (**3) Diffusion Period (May 25 - May 26)**: During this phase, new issues and developments related to the incident began to surface, especially within the new media environment. The uncontrollable nature of the information channels led to the emergence of new narratives, often as "breaking news." This further fueled the crisis, allowing the negative impacts to spread and maintain the issue's momentum, thereby triggering the potential for a secondary outbreak. **(4) Pacification Period (May 27 - May 31)**: The public opinion surrounding the incident gradually subsided as the crisis was resolved. The negative impacts were mitigated, and both Cathay Pacific and the wider social system began to return to normalcy.

**A. Time Series Analysis**

Time-series analysis provides a robust framework for identifying causal and temporal dependencies in agenda-setting research (De Gooijer & Hyndman, 2006). The Autoregressive Integrated Moving Average (ARIMA) model combines autoregressive (AR), differencing (I), and moving-average (MA) components to address nonstationarity and short-term volatility in time-dependent data (Box et al., 2015). Compared with other statistical approaches frequently applied in communication studies, such as Vector Autoregression (VAR) and Structural Equation Modeling (SEM), ARIMA offers distinct methodological advantages for this research context. VAR assumes symmetric relationships among multiple stationary variables and is more suitable for modeling long-term equilibrium systems (Lütkepohl, 2005). SEM, on the other hand, focuses on latent constructs and cross-sectional associations but fails to capture temporal autocorrelation or evolving dependencies across time (Kline, 2016).

In contrast, ARIMA excels in modeling univariate or short-span sequential processes that exhibit temporal fluctuations and irregular shock patterns—typical of crisis communication cycles where issue salience and public attention change rapidly. By emphasizing lag structure and temporal prediction rather than contemporaneous correlation, ARIMA aligns conceptually with the temporal agenda-setting perspective, which seeks to understand when and how long media–public interactions exert influence (Tang & Chen, 2022; Neuman et al., 2014). Therefore, this study employs the ARIMA model to capture time-dependent variations and forecast agenda evolution during crisis events in China's hybrid media ecosystem.

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### B. Social Network Analysis

By integrating Social Network Analysis (SNA) with ARIMA modeling, this study examines the structural and temporal relationships between traditional media, social media, and the public during crisis events. While traditional agenda-setting studies typically conceptualize influence as a linear flow between actors, the networked communication environment exhibits multidirectional, feedback-driven relationships (Vargo & Guo, 2016). SNA extends beyond this linear framework by visualizing how agendas propagate through relational ties—such as reposts, mentions, and shared issue frames—across platforms (Arman & McClurg, 2024).

In this study, SNA complements ARIMA by mapping the structural dimension of agenda alignment, while ARIMA captures the temporal evolution of these relationships. The combination provides both a static and dynamic view of agenda-setting, enabling the identification of reciprocal influence patterns between communication entities. To quantify these relationships, the Quadratic Assignment Procedure (QAP) correlation index was applied to measure agenda similarity between traditional media, social media, and the public across four crisis stages: latent, outbreak, diffusion, and pacification. As presented in Table 2, the QAP indices exhibit apparent temporal variations in the strength of agenda interaction.

**Table 1.** Classification of Public Opinion Time Stages and Stage-Specific Agenda Interaction Index

| Stages of Public Opinion Development | Latent Period | Outbreak Period | Diffusion Period | Pacification Period |
|---|---|---|---|---|
| ***Forward Agenda*** | | | | |
| QAP Index Between Traditional Media and the Public | 0.476 | 0.288 | 0.185 | 0.577 |
| QAP Index Between Social Media and the Public | 0.600 | 0.602 | 0.343 | 0.237 |
| ***Reverse Agenda*** | | | | |
| QAP Index Between the Public and Traditional Media | 0.290 | 0.225 | 0.383 | 0.531 |
| QAP Index Between the Public and Social Media | 0.507 | 0.473 | 0.387 | 0.223 |

Source: Researcher (2025)

Based on Table 1, during the latent stage (May 21–22), social media exhibits the highest forward-agenda correlation with the public (QAP = 0.600), serving as the primary driver of issue emergence. This dominance persists throughout the outbreak period (May 23–24) (QAP = 0.602), whereas traditional media remains less responsive (QAP = 0.288). In the diffusion stage (May 25–26), both agenda correlations weaken, suggesting fragmentation and saturation of public attention. In the pacification phase (May 27–31), traditional media reasserts influence (QAP = 0.577), reflecting its delayed but stabilizing effect on public discourse.

Reverse-agenda results further reveal that the public exerts a more substantial influence on social media agendas early in the crisis (QAP = 0.507 in the latent phase) but increasingly shapes traditional media narratives in later stages (QAP = 0.531 in pacification), as shown in Table 1. These findings highlight a temporal power shift: social media dominates initial discourse formation, while traditional media consolidates narrative control as events stabilize. This evolving dynamic supports a hybrid agenda-setting model where influence alternates rather than flows unidirectionally (Vargo & Guo, 2016).

### C. Smoothness Analysis and Lag Order Determination

Before applying ARIMA modeling, it was essential to ensure that the time-series data satisfied the stationarity assumption, meaning that its statistical properties—such as mean, variance, and autocorrelation—remained stable over time. To verify stationarity, the analytical process proceeded through data preprocessing, stationarity testing, differencing, and lag-order determination. For this study, the Augmented Dickey–Fuller (ADF) test was employed for each agenda-series variable. The ADF test examines whether a time series contains a unit root, indicating non-stationarity. A p-value below 0.05 allows for rejection of the null hypothesis of a unit root, confirming that the series is stationary. A higher p-value suggests the need for differencing to remove trend effects and achieve stability. Compared to the standard Dickey–Fuller test, the ADF test incorporates lagged terms to account for residual autocorrelation, making it more suitable for complex time-series data with communication components (Zhang et al., 2014).

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**Table 2.** ADF Test Results for QAP-1 (Traditional Media and the Public)

| Order of Differencing | t | p | Critical Values | | |
|---|---|---|---|---|---|
| | | | *1%* | 5% | 10% |
| 0 | -1.142 | 0.698 | -3.456 | -2.873 | -2.573 |
| 0 | -1.142 | 0.698 | -3.456 | -2.873 | -2.573 |

Source: Researcher (2025)

As presented in Table 2, the QAP-1 sequence (traditional media–public relationship) was initially non-stationary (t = –1.142, p = 0.698), but achieved stability after first-order differencing (d = 1), with a test statistic of t = –7.993, p = 0.000, significant at the 1% level. This confirms that differencing effectively transformed the data into a stationary process, ensuring validity for subsequent modeling. Following stationarity confirmation, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots—analyzed in SPSS—were used to identify the optimal lag structure. The plots suggested an autoregressive order (p = 1) and a moving average order (q = 1). After comparative testing, the final model was determined as ARIMA (3,1,1), with first-order differencing representing the stabilized series. This configuration yielded white noise residuals, meeting the statistical requirements for robust time-series forecasting.

## D. Autoregressive Integrated Moving Average Model (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model, also known as the Box–Jenkins model, is a widely applied approach in time-series analysis, particularly effective for modeling non-stationary data with trends and seasonal variations (Box et al., 2015). The model is expressed as ARIMA (p, d, q), where p denotes the autoregressive order, d represents the degree of differencing, and q indicates the moving-average order.

The first step in ARIMA modeling involves differencing the data to achieve stationarity, ensuring that the series's mean, variance, and autocorrelation remain constant over time. Stationarity was verified through the Augmented Dickey–Fuller (ADF) test and visual inspection of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Once the series exhibited rapid convergence toward zero, model parameters were finalized. In this study, iterative testing of the ACF and PACF plots determined the optimal configuration as ARIMA (3,1,1)—with first-order differencing (d = 1) — ensuring stability and eliminate unit roots.

As shown in Figure 3, the panels present the time-series agenda relationships and the corresponding prediction results for each of the four key agenda interactions: (1) The relationship between traditional media and the public (top left), (2) The relationship between social media and the public (top right), and (3) The reverse agenda relationships between the public and traditional media (bottom left), and between the public and social media (bottom right).

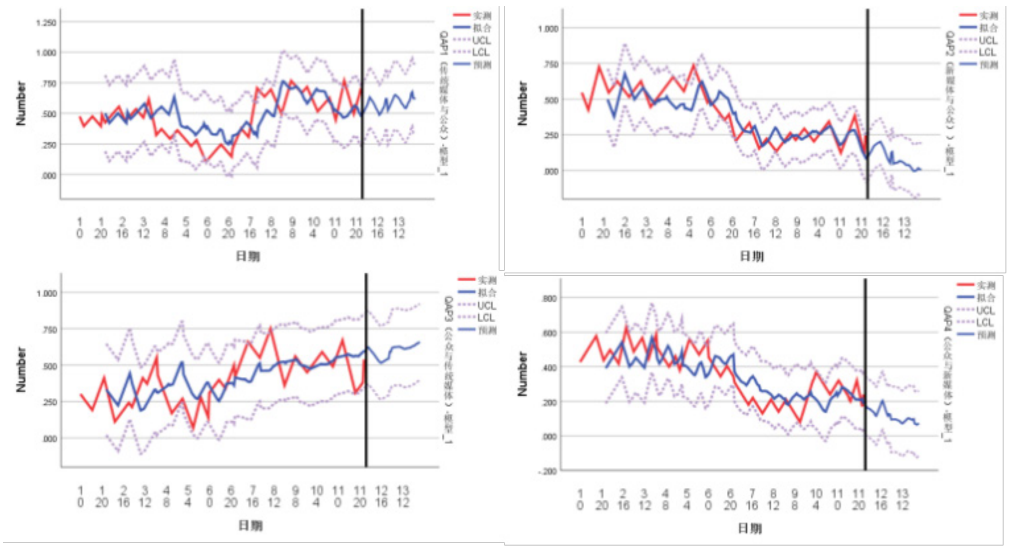


**Figure 3.** Time-Series Agenda Status and Future Prediction Results Based on the ARIMA Model
Source: Researcher (2025)

These panels illustrate the outcomes of the ARIMA model construction, including regression coefficients, p-values, and other relevant statistics. It is essential to note that while the size of p-values may not always be the primary focus—especially if they exceed the conventional 0.05 threshold—the formulation of model parameters is tailored to

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the specific settings and needs of the model. To assess the model's fit, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used for model comparison. Generally, smaller values of AIC and BIC indicate a better-fitting model. By comparing changes in these values across multiple iterations, the optimization process of the model is better understood.

The ARIMA model formula, based on the (3,1,1) parameters and 1st-order differenced data, is expressed as:

$$y(t)=0.000+0.400*y(t-1)+0.248*y(t-2)-0.077*y(t-3)+0.239*\varepsilon(t-1)$$

Where y(t) represents the agenda relevance index, and ε(t-1) is the residual from the previous time period. The Q statistic results show that if the p-value of Q6 is greater than 0.1, the null hypothesis cannot be rejected at the 0.1 significance level. This suggests that the residuals of the model are white noise, indicating that the model meets the required analytical assumptions.

To address the first and second research questions, a time series of agenda relevance indices was constructed over 11 days. Predictions were made for the 12th and 13th days to answer the third research question. The results of the time-series analysis reveal distinct temporal patterns in the interactions between media agendas and public influence. The forward agenda level indicates that the effectiveness of the traditional media agenda is expected to show a steady, though modest, increase over the next two days, suggesting that mainstream media continue to shape public discourse even as digital dynamics evolve. In contrast, the social media agenda exhibits a clear downward trajectory during the same period, suggesting a temporary decline in its ability to influence issue salience.

Meanwhile, the reverse agenda level highlights the evolving role of public feedback in shaping media content. The public's influence on traditional media displays fluctuations but maintains an overall upward trend, reflecting the increasing responsiveness of mainstream outlets to audience sentiment. Conversely, the public's impact on social media agendas fluctuates but generally declines, suggesting a saturation point where user engagement becomes less effective in driving agenda changes. Collectively, these trends underscore the complex and asymmetrical temporal dynamics between traditional and social media in the agenda-setting process.

During the issue diffusion process, multiple peaks emerge, indicating key points of heightened attention and concern. These peaks are significant because their appearance at different stages reveal when issues gain public attention. Issues that peak earlier indicate a faster rise in attention. Analyzing these sequential peaks helps identify which agendas are leading the discourse. Social media is the most responsive platform for reflecting shifts in public opinion. However, during the opinion calming phase, the public's reverse influence on social media is notably limited, suggesting that social media becomes less receptive to public influence as the crisis stabilizes.

## E. Granger Causality Test Analysis

In this study, the focus is on the Cathay Pacific Airways incident. Here, the null hypothesis (H1) is that incorporating past data from both traditional and social media improves the prediction of the social media agenda relative to using only past social media data, indicating that the traditional media agenda is a Granger cause of the social media agenda. This would mean that traditional media contributes to changes in the social media agenda.

Before conducting the Granger causality test, it is essential to confirm that the time series data is stationary. This is typically achieved through an Augmented Dickey-Fuller (ADF) test, which ensures the reliability of the data used in the analysis. The Granger causality test results are interpreted based on the following criteria: (1) If the p-value is less than 0.05, the null hypothesis is rejected, indicating that X1 is a Granger cause of X2, and (2) If the p-value is greater than 0.05, the null hypothesis is accepted, meaning X1 is not a Granger cause of X2.

**Table 3.** Granger Test Results

| Null Hypothesis H0 | F-Value | p-Value | df1 | df2 |
|---|---|---|---|---|
| Null Hypothesis H1: 'QAP-1 (Traditional Media and the Public)' is not the Granger cause of 'QAP-2 (Social Media and the Public).' | 0.473 | 0.624 | 2 | 0.473 |
| Null Hypothesis H2: 'QAP-2 (Social Media and the Public)' is not the Granger cause of 'QAP-1 (Traditional Media and the Public).' | 7.112 | 0.001** | 2 | 7.112 |
| Null Hypothesis H3: 'QAP-3 (The Public and Traditional Media)' is not the Granger cause of 'QAP-4 (The Public and Social Media).' | 4.155 | 0.017* | 2 | 4.155 |
| Null Hypothesis H4: 'QAP-4 (The Public and Social Media)' is not the Granger cause of 'QAP-3 (The Public and Traditional Media).' | 2.294 | 0.103 | 2 | 2.294 |

Source: Researcher (2025)

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Based on Table 3, the p-value threshold in this study was determined at the researcher's discretion, with a default lag order set to 2. The Granger causality test results reveal distinct directional relationships among traditional media, social media, and public agendas. For QAP-1 (traditional media and the public) versus QAP-2 (social media and the public), the p-value is 0.624 (> 0.05), leading to the acceptance of the null hypothesis. This indicates that the traditional media agenda does not Granger-cause the social media agenda. Conversely, for QAP-2 (social media and the public) versus QAP-1 (traditional media and the public), the p-value is 0.001 (< 0.05), indicating rejection of the null hypothesis and confirming that the social media agenda significantly influences the traditional media agenda. Regarding public-related agendas, the p-value for QAP-3 (public and traditional media) versus QAP-4 (public and social media) is 0.017 (< 0.05), suggesting that the public's agenda concerning traditional media affects its agenda for social media. In contrast, the reverse relationship (QAP-4 vs. QAP-3) yields a p-value of 0.103 (> 0.05), indicating that there is no significant influence of the public's social media agenda on its traditional media agenda.

As summarized in Table 3, these findings indicate that Granger causality exists for some agenda relationships but not for others. Specifically, traditional media do not significantly shape the social media agenda. In contrast, social media has a notable influence on traditional media, particularly during the latency period of public opinion formation, supporting prior studies that highlight social media's dominant agenda-setting role. Moreover, the public's agenda related to traditional media appears to influence its engagement with social media, but the reverse effect is not observed. Collectively, these results address Research Question 1, illuminating the complex and asymmetrical dynamics of agenda setting among traditional media, social media, and the public during crisis events.

## F. Key Characteristics of the Chronological Agenda

### 1. Significant Lag in Agenda Effectiveness of Traditional Media During the Latent Stage of Public Opinion

The analysis reveals a distinct delay in the agenda-setting effectiveness of traditional media compared to social media during the latent stage of public opinion formation. This finding aligns with previous research suggesting that social media platforms play a critical role when traditional communication systems fail or are absent (Hidayat et al., 2024). The time-series trend shows that social media reached its peak agenda effectiveness at approximately 20:00 on the first day. In contrast, traditional media's peak effectiveness occurred only around 12:00 on the third day, creating a 40-hour gap between the two. Social media's rapid response capabilities allow it to capture public attention early in the opinion formation process. In contrast, traditional media's slower response to sudden events reflects the inherent delays in its information processing and dissemination mechanisms.

This delayed response not only limits the influence of traditional media in shaping public opinion but also contributes to the spread of misinformation and irrational views. Unlike previous studies that observed only a one- to seven-day delay in Western election contexts (Roberts et al., 2002; Conway et al., 2015), this study finds that traditional Chinese media exhibit a longer temporal gap, reflecting stricter gatekeeping and hierarchical information flow. During the critical initial phase of public opinion development, the public's demand for timely and accurate information reaches its peak. When traditional media fail to provide such information promptly, an information vacuum emerges, fueling the spread of rumors and unverified claims (Vosoughi et al., 2018; Sunstein, 2014).

Therefore, this study suggests that future research should focus on optimizing the information processing workflows of traditional media to improve their response times during crisis events. By enhancing traditional media's capacity for quick and effective engagement, it will be better positioned to guide public opinion more constructively and play a more significant role in shaping public discourse (Waisbord, 2018).

### 2. Decline in Social Media Agenda Effectiveness in the Middle and Late Stages of Public Opinion

A thorough analysis of the graphical temporal trends clearly shows that social media's influence on agenda-setting peaks during the early stages of public opinion development, particularly in the latent and initial outbreak phases. During these stages, the dynamic and interactive nature of social media is fully activated, enabling it to play a central role in shaping and steering public discourse.

However, as public opinion progresses into the diffusion and stabilization stages, the agenda-setting effectiveness of social media begins to wane. Its ability to maintain public attention and sustain meaningful discourse diminishes substantially compared to its influence during the early stages of opinion formation. This trend underscores the empowering role of social media, particularly in its initial impact and unique mechanisms of engagement (Tufekci, 2017). The observed temporal decay aligns with previous findings that Twitter's influence tends to wane as traditional media coverage consolidates dominant narratives (Conway et al., 2015). However, this study extends that observation by revealing a more rapid decline within China's networked environment, where algorithmic curation accelerates topic fatigue and shortens the lifespan of public discourse.

Social media enables the public to engage in discussions, disseminate information, and diffuse topics at any time and from anywhere, thereby bypassing traditional information pathways and cognitive processes (Baharuddin et al.,

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2022). This transition highlights the evolving influence of social media across the public opinion cycle. It also suggests that future research should investigate how to harness social media's empowering properties better to foster healthy, rational public discourse. Moreover, strategies need to be developed to sustain or enhance social media's agenda-setting effectiveness as public opinion matures (Vosoughi et al., 2018).

**3. Variability of Public Agenda Effectiveness Across Different Stages of Public Opinion**

This study demonstrates that public reverse agenda-setting plays a significant role within the broader agenda-setting network, with the public actively influencing both social media and traditional media agendas. This highlights the evolving complexity of the media ecosystem, where agenda-setting is no longer a simple, one-way process, but instead involves a dynamic interaction among multiple stakeholders.

However, the public's effectiveness in influencing reverse agenda-setting through social or traditional media varies considerably across different stages of public opinion development. Analysis of graphical temporal trends reveals that during the latent and outbreak periods, the public's influence is most evident at the social media level. This can be attributed to social media's ability to quickly reflect public opinions (Vosoughi et al., 2018; Zhao & Zhang, 2023). This dynamic departs from the linear, one-way transmission models of early communication theory (Katz & Lazarsfeld, 1955), and from McCombs' hierarchical framing of media influence. Instead, it reveals a cyclical feedback system unique to China's hybrid media ecology. In contrast, traditional media often respond more slowly to public sentiment in these early stages (Ju, 2008; Waisbord, 2018).

As public opinion progresses into the diffusion and stabilization periods, the public's influence shifts towards traditional media. This change is partly due to the unique characteristics of traditional media and their role in shaping public discourse. Traditional media are more inclined to emphasize and amplify public opinion during these later stages, resulting in variability in the influence of the public agenda across different phases of public opinion development (McCombs, 1972; Riezebos et al., 2011; Salman et al., 2016).

**4. Future Trends in Agenda Effectiveness During the Middle and Late Stages of Public Opinion**

In the case of the Cathay Pacific incident, predictions for agenda effectiveness on days 12 and 13 indicated that the level of change during these days remained relatively stable, with no significant fluctuations. This suggests a trend of stabilization in both the importance of the issues and the public's attention as the incident progressed into its later stages. Such stability likely reflects a convergence in public perception over time, leading to a diminished sense of novelty surrounding the issue. This, in turn, impacts the effectiveness of agenda-setting.

The alignment between predicted and observed trends in the later stages of public opinion further supports the robustness of the research methodology and analytical model in capturing the evolving dynamics of public opinion and agenda-setting, demonstrating its utility for crisis communication analysis. This consistency suggests that public attention and media coverage may become more focused on a few central issues, with the discussions reaching a point of saturation (Vargo et al., 2017).

Lastly, the ability to predict trends in public opinion and agenda effectiveness provides crucial insights for managing public opinion and crisis communication. Understanding how agenda effectiveness evolves is essential for crafting effective communication strategies, guiding public discourse, and managing public relations crises (Waisbord, 2018). These studies not only highlight the value of using time-series analysis to predict public opinion trends but also underscore the importance of examining the interaction between media coverage and public attention, particularly in the context of crisis management.

**5. Social Media Agenda as a Catalyst for Changes in Traditional Media Agenda**

This study highlights the distinct roles of social media and traditional media in shaping the public agenda at each stage of public opinion development. Notably, it shows that social media not only shape the public agenda but also drive changes in traditional media agendas. The Granger causality analysis suggests that, during this crisis, social media agendas played a significant role in shaping traditional media agendas, whereas traditional media did not exert a reciprocal influence on social media agendas (Vosoughi et al., 2018; Waisbord, 2018). In the digital era, agenda-setting among various media entities is highly interactive. Despite this, one entity often emerges as the dominant force, influencing the agendas of others. In this case, social media have proven to be a powerful driver in shaping the direction and focus of traditional media agendas (Tufekci, 2017).

## G. Strategic Value of the Temporal Agenda Mechanism for Guiding Public Opinion

During crisis events, individuals often struggle to fully comprehend the situation, leading them to rely heavily on social media and other rapid information channels. This creates a dynamic and complex public opinion environment

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where both accurate and inaccurate information coexist and influence public perceptions (Tandoc et al., 2018). Given this complexity, it is essential to apply the agenda-setting framework across different stages of public opinion, especially during crises. Understanding the time dimension of agenda-setting can significantly improve the management of public discourse. By examining the relationship between media agendas and the public agenda, we can more effectively align official communications with public sentiment and direct the flow of information throughout the crisis (Tong, 2025).

**1. Proactively Responding to Public Concerns and Advancing Agenda Setting**

Traditional media must take a proactive role in responding to public concerns during crises. The key to managing public opinion is not to suppress, but to channel it effectively (Reynolds & Seeger, 2005; Aldamen & Hacimic, 2023). Given the public's increased freedom to express their views, there is a risk that unaddressed concerns may get out of control. By shaping public perceptions early on, traditional media can play a pivotal role in fostering rational discourse and promoting a safer, more harmonious society (Daud, 2021). Therefore, during a crisis, traditional media should lead in agenda-setting, using their authority and resources to guide the narrative and mitigate misinformation.

**2. Synergistic Collaboration Among Diverse Media to Lead Agenda Setting**

As a crisis unfolds and public opinion spreads, the synergy between different media platforms is crucial for effective agenda-setting. As social media's influence on traditional media continues to rise gradually, a delay in traditional media's responsiveness can allow irrational opinions to gain traction. The ability to set the agenda swiftly is a key determinant of successful public opinion management. Emotional narratives on social media can shift public attention and intensify crisis discourse, underscoring the need for timely intervention by traditional media to restore balance (Dusi & Lacalle, 2024). Future research should investigate how multiple media can collaborate to effectively manage this complex dynamic (Bennett & Segerberg, 2012).

**3. Tailored Guidance for Different Public Opinions and Restoration of Sensitive Issues**

The media must adapt their strategies to guide public opinion across different stages of a crisis. By categorizing and guiding these opinions, the media can facilitate the restoration process and promote positive discourse during the recovery phase (Guo & McCombs, 2016; Vargo et al., 2017). The press or media can guide or influence its audience's views by selectively presenting information and interpreting events (Alamsyah, 2024). Strategic issue replacement can help shift public focus from negative to positive narratives. By showcasing positive actions and restorative measures, the media can encourage productive conversations, increase the frequency of information updates, and steer public attention towards more constructive topics (Kim, 2016). Although this study focuses on social media platforms, expanding the research scope to include additional media channels will provide a more comprehensive understanding of these dynamics.

## CONCLUSION

This study employs agenda-setting theory as its theoretical foundation and utilizes the public opinion lifecycle theory as its analytical framework. By integrating time-series analysis, text mining, social network analysis, and Granger causality inference, it empirically investigates the temporal relationship between leadership and followership in agenda-setting during emergencies across traditional media, social media, and individual users. The findings reveal that media–public interactions evolve through distinct lag structures and reciprocal influence cycles, offering new insights into the dynamic evolution of public opinion in crisis contexts and providing a theoretical basis for more effective guidance of public opinion. This research extends classical agenda-setting frameworks into the temporal and algorithmic communication era, demonstrating that time functions not merely as a context but as a structural driver of influence. It showcases the value of combining ARIMA time-series modeling and social network analysis to capture nonlinear and feedback-driven communication dynamics.

Furthermore, the findings provide a scientific reference for crisis communication governance, suggesting that understanding the timing and lag of cross-platform agenda shifts can help governments and media organizations preempt misinformation, synchronize crisis narratives, and enhance public trust through early, coordinated engagement. In broader terms, this research contributes to both scholarly discourse and social governance. Academically, it deepens understanding of how communication timing shapes the flow of influence in digital public spheres, advancing a computational and temporal turn in agenda-setting research. Socially, it offers evidence-based insights for improving the responsiveness and resilience of crisis communication systems in the algorithmic media environment. By illuminating when and how media and public attention interact, this study ultimately supports the development of a more transparent, rational, and participatory model of public discourse in times of crisis.

Despite its contributions, this study has several limitations, including the fact that the data are primarily drawn from Weibo interactions, which may not fully capture cross-platform discourse. Therefore, future studies could integrate multi-platform datasets or employ mixed methods such as interviews and surveys to triangulate findings. While the current model emphasizes temporal lag analysis, incorporating psychological or affective dimensions could further illuminate how emotions mediate the evolution of agendas. Lastly, expanding the scope of crisis types and cross-national

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comparisons would enhance the generalizability of temporal agenda-setting dynamics.


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