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Utilizing Time Series Analysis to Understand the Effects of Social Media Activities on Public Opinion over Time

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ABSTRACT

This study explores the dynamic relationship between social media activities and public opinion through time series analysis, utilizing extensive datasets from 2018 to 2024 that encompass over 1.5 million social media posts and opinion poll data. Using Vector Auto regression (VAR) models and structural time series analysis, the research reveals significant patterns indicating that specific types of social media engagement can precede shifts in public sentiment by 2 to 8 days, particularly in areas that provoke political polarization. The results highly recommend focusing not on the frequency of posts but on engagement metrics as a basis for the proper assessment of public opinion changes. This shows the crucial role of social media in developing public opinion that immediately affects political campaigning, advertising, and social science, among other fields. The methodology of the research served as a basis for creating a reliable tracking and, possibly, predicting mechanism that can trace the changes in social consensus due to the popularity of some topics in digital space.

INTRODUCTION

The emergence of social media platforms has significantly changed the way we create, share, and consume information in today's world. What started as basic communication tools has transformed into intricate ecosystems that play a crucial role in news dissemination, political discussions, and public debates. By 2025, it's estimated that approximately 4.8 billion users will be active on these platforms (Statista, 2024), spending an average of 2.5 hours daily browsing through content. This digital evolution has shifted the traditional power dynamics in public discourse. Unlike conventional media, which usually presents information in a one-way manner from centralized sources to passive audiences, social media encourages a two-way conversation, prompting users to engage actively. This setting empowers individuals to create, amplify, or question narratives that influence our shared understanding of important issues, from public health to political ideologies.

Understanding how social media activity shapes public opinion is becoming increasingly crucial. It enables us to understand the dynamics of social influence in our digital era, provides valuable insights for stakeholders such as policymakers and businesses, and raises important questions about the state of democratic discourse, particularly when traditional information gatekeepers are often overlooked

The problem statement highlights the significant methodological challenges encountered when trying to measure and understand the impact of social media on public opinion. One of the main difficulties is the vast complexity and volume of data generated by social media platforms, which makes it hard to collect and analyze everything thoroughly. Additionally, the way online discussions and public sentiment change over time involves intricate lag structures and feedback loops that simple correlation analyses fail to capture

Another significant challenge is identifying causal relationships. Distinguishing genuine causal links from mere correlations is tricky, as both social media activity and public opinion can be influenced by external events occurring simultaneously. The issue of measurement validity is significant; the emotions shared on social media may not accurately represent the broader public sentiment due to demographic biases and the way algorithms filter content on each platform

Moreover, integrating theoretical frameworks with practical findings necessitates collaboration across various disciplines, including computer science, communication studies, and political science. This study aims to address the research gaps caused by challenges in analyzing large datasets over time through rigorous time series analysis. The study has four main objectives. Firstly, it intends to explore the relationship between social media traffic and changes in public perception over a long period, utilizing advanced time series analysis techniques. Second, the study plans to pinpoint specific types of social media indicators—like volume metrics, engagement metrics, and sentiment indicators—that are most effective in forecasting shifts in public sentiment. Third, the research will create a methodological framework to distinguish between correlation and causation regarding how digital platforms influence public opinion. Finally, it seeks to assess how the unique characteristics of different

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LITERATURE REVIEW

To better understand how the media shapes public perceptions, particularly in relation to social media, this literature study examines various theoretical perspectives. One of the key hypotheses is the Agenda-Setting Theory, which was first put forth by McCombs and Shaw in 1972 and maintains that the media's emphasis on a certain issue can affect the public's perception of its significance. In the context of social media, the concept has broadened to encompass the impact of user-generated material and algorithmic boosts on the topics that become popular (Barberá *et al.,* 2019). Social media is essentially a tool for agenda-setting, both through professionally created content and by collective user-generated actions that highlight certain issues.

According to Noelle-Neumann's (1974) Spiral of Silence hypothesis, individuals who believe their opinions are in the minority are less inclined to express them, creating a cycle where prevailing views appear to be more widespread than they actually are. Depending on the features of the platform and the makeup of its user groups, this influence on social media may be increased or decreased (Hampton *et al.,* 2014). This idea is especially useful for comprehending how people's online and offline thinking sharing might be influenced by their impressions of public opinion on social media. According to Katz and Lazarsfeld's (1955) Two-Step Flow of Communication model, leaders of opinion frequently interpret messages for their social circles, allowing media power to flow via them. Social media has transformed this dynamic by enabling everyday users to become micro-influencers, which can accelerate the dissemination of opinions (Wu *et al.,* 2011, Adegbenro & Akinola 2025).

This framework highlights how certain users can significantly affect sentiment changes within their follower networks. Selective Exposure Theory indicates that people tend to seek out information that aligns with their pre-existing beliefs while avoiding anything that contradicts them (Stroud, 2010, Joshua & Egbe 2025). Social media algorithms can enhance this behavior by creating personalized information environments that limit our exposure to diverse viewpoints (Pariser, 2011).

It's crucial to understand how "filter bubbles" affect the way our opinions are shaped and influenced by various platforms, as this is central to the research we're conducting. The Network Theory of Public Opinion, which has gained popularity recently, highlights how intricate spreading mechanisms within interconnected social networks shape individual beliefs (Watts and Dodds, 2007). Social media platforms offer special chances to investigate these sites in real time and on a wide scale. Despite being created in the early days of social media, these theoretical frameworks are essential for comprehending the ways in which digital communication might influence the creation of collective opinions. However, new analytical approaches and strong empirical proof are needed to apply them to the present social media ecosystem.

Research in this area has developed quickly over the last few decades, using a variety of techniques to examine the connection between public perception and social media. Public opinion and social media measures were found to be correlated in early descriptive research. For instance, Ceron *et al.* (2014) noted comparable patterns in a number of European nations, while O'Connor *et al.* (2010) discovered moderate connections between presidential approval ratings and Twitter mood. Although these research laid the groundwork for using social media as a stand-in for public opinion, they frequently failed to account for time constraints or other potential confounding variables. In the meantime, natural experiments or instrumental variables using complex designs were used in quasi-experimental studies to support causal claims. For instance, King *et al.* (2017) conducted a large-scale field experiment across 48 Chinese social media platforms, revealing that government-sponsored posts significantly influenced the overall emotional tone of online discussions, even though they did not substantially alter specific opinions. Similar to this, Bond *et al.* (2012) carried out a large-scale Facebook experiment that showed how voting and other practical actions can be influenced by societal pressure within networks. The use of Natural Language Processing (NLP) tools for sentiment analysis has advanced throughout time. Simple lexicon-based methods have given way to increasingly intricate deep learning models that take emotional subtleties and context into account. Muhammad (2018).

Nonetheless, Cody *et al.* (2015) pointed out that there are ongoing difficulties in precisely expressing political mood, especially when it comes to identifying nuanced changes in viewpoint as opposed to only binary classifications. Time series analyses have been used by researchers to look at how social media and public opinion have changed over time. In order to ascertain if Twitter mentions may forecast German election results, for example, Jungherr *et al.* (2012) employed Granger causality tests; however, they discovered no evidence in favor of social media as a leading indicator. More recently, Xiong *et al.* (2019) investigated the impact of Twitter sentiment on cryptocurrency prices using Vector Autoregression (VAR) models, finding substantial predictive connections across different time lags. In order to distinguish the effects of various social media platforms, cross-platform studies have started. Although rigorous comparisons are still required, Bossetta (2018) looked at the design elements of Facebook, Instagram, Snapchat, and Twitter during political campaigns and suggested that each platform's distinct features have a major impact on how content influences users. Criticisms of methodology have sparked worries; for example, sample bias in social media data can lead to erroneous conclusions about popular sentiment, according to Scharkow and Vogelgesang (2011). Mellon and Prosser (2017) discovered systematic differences between social media users and the general population, raising questions about the reliability of sentiment analysis based on these platforms. The critiques highlight how crucial it is to maintain scientific rigor and cross-reference data. Even though the industry has advanced significantly, this analysis shows that many questions remain about the complex relationship between social media activity and changes in public opinion. More advanced time series techniques, in particular, may help to shed light on causality problems that are frequently missed by simple correlational investigations.

Although a number of time series analysis techniques have been applied to social media data, their use in gauging public opinion is still in its infancy. Trend forecasting is a common application for ARIMA models. For instance, Asur and Huberman (2010) found that social media indicators were more dependable than conventional market metrics when they used ARIMA models to forecast movie box office success based on Twitter mentions. Nevertheless, univariate ARIMA models have trouble capturing the intricate relationships between several time series, which restricts their capacity to comprehend bidirectional influences (Box *et al.,* 2015). On the other hand, Vector Auto Regression (VAR) models work especially well for investigating these connections without requiring rigorous assumptions about causality direction. In the 2009 German federal election, for example, Jungherr (2014) examined the relationship between Twitter attention and polling results using VAR models, finding evidence of mutual interaction. In a similar vein, Abney *et al.* (2019) used VAR to examine the relationship between stock prices and Twitter sentiment regarding companies, revealing complicated lag structures and nuanced bidirectional correlations. By breaking down time series into trend, seasonal, and irregular components, structural time series models use a different strategy that enables a more in-depth examination of underlying patterns. In order to predict causal impacts in time series data, Brodersen *et al.* (2015) created Bayesian structural time series models. These models have been used to assess how social media campaigns affect conversion metrics. This method shows great potential for isolating the influence of specific social media events on shifts in public opinion.

Another important statistical idea that examines whether one time series can predict another is Granger Causality Testing. Social media research has made great use of this approach. Granger causality tests, for instance, were utilized by Garcia *et al.* (2017) to show that social media emotional reactions frequently preceded financial market swings. Granger causality, however, creates predictive associations rather than actual causation, as Pearl (2009) notes. Furthermore, wavelet analysis and Panel Vector Autoregression offer useful techniques for investigating temporal patterns and heterogeneity. Despite their limited use in the study of social media influence, Canova and Ciccarelli (2013) demonstrated how these models may handle variances among units while still discovering common dynamic trends.

In a similar vein, Kwon *et al.* (2017) used wavelet analysis to investigate the dissemination of information through social networks in times of crisis, exposing unique propagation patterns at various points in time. The intricate, non-linear correlations found in social media data could be captured by recent developments in deep learning, particularly with Long Short-Term Memory networks. For example, Phillips *et al.* (2017) showed that deep learning models, as opposed to conventional time series models, may more reliably anticipate public health risks based on social media signals. Overall, even though time series techniques have been used successfully, there is still a lot of room for more sophisticated applications that concentrate on public opinion dynamics.

MATERIALS AND METHODS

Data Collection

The study collected data using a thorough methodology that lasted 72 months, from January 2018 to December 2023.

Three major social media platforms—Facebook, Reddit, and Twitter/X—provided the data for this study, which focused on 10 different public interest themes like immigration, healthcare policy, and climate change. They used the Academic Research API to gather 850,000 tweets on Twitter/X alone, monitoring data such as favorite and retweet counts. Reddit donated 225,000 submissions and comments using the Push Shift API, and Facebook contributed 425,000 public posts collected via Crowd Tangle. A strong validation approach supported the selected themes, which led to a high inter-coder reliability coefficient.

The validity of the measurements was ensured by measuring public opinion through a number of reputable polling companies, such as Gallup and the Pew Research Center, in addition to social media data. The data for this study, which focused on ten distinct public interest issues like immigration, healthcare policy, and climate change, came from three significant social media platforms: Facebook, Reddit, and Twitter/X. They collected 850,000 tweets on Twitter/X alone using the Academic Research API, tracking metrics like favorite and retweet counts. Facebook contributed 425,000 public posts gathered using Crowd Tangle, and Reddit donated 225,000 submissions and comments via the Push Shift API. The chosen topics were supported by a robust validation process, resulting in a high inter-coder reliability coefficient.

In addition to social media data, public opinion was measured by many credible polling firms, including Gallup and the Pew Research Center, to guarantee the legitimacy of the measurements.

Data processing

The data processing section describes how polling data and social media analytics were retrieved and examined. Social media metrics were first divided into four primary categories: sentiment, network, engagement, and volume metrics. Volume measures include the quantity of posts, the number of distinct authors, and the frequency of publishing. Total interactions, engagement rates, and the virality of a post are all examined by engagement metrics. Network metrics explore the depth of information cascades, the centrality of debates, and cross-ideological interaction. A transformer-based NLP pipeline driven by RoBERTa was employed for sentiment measures, which have been shown to be more accurate than the traditional lexicon-based techniques.

In the second section, the topic of how to generate opinion metrics from polling data was covered. This involves gauging salience, polarization, opposition, and support levels. These indicators were standardized using item response theory models to ensure that they are similar across different polling sources. Gaussian process regression was then used to create a daily time series for every metric.

Lastly, a full description of the time series preparation methods was provided. This entails utilizing transformations to make sure all series are stationary, using STL decomposition to account for seasonality, using interquartile range techniques to deal with outliers, and using predictive mean matching to fill in any missing data. It was also emphasized how crucial it is to align the time series data in order to precisely link social media indicators with opinion data, keeping in mind the polling dates and social media timestamps.

Analysis Method

The analytical method investigated the relationship between social media metrics and opinion indicators by utilizing a variety of time series approaches. Vector Auto regression (VAR) models, which were created to capture the dynamic interactions at work, were at the center of this investigation. The Akaike Information Criterion (AIC) was used to establish the appropriate lag orders for these models, which contained a combination of social media metrics and opinion indicators. These lag orders frequently fell between 5 and 14 days, indicating that the impacts may endure anywhere from one to two weeks. Granger causality tests were performed inside the VAR framework to investigate the predicted links between opinion indicators and social media data.

The timing and dynamics of these interactions were investigated using Impulse Response Functions (IRFs), which demonstrate the magnitude, latency, persistence, and overall influence of shocks on opinion values in social media measures. The assessment of these replies' statistical significance was strengthened by the use of bootstrapping techniques to create confidence intervals for them.

In order to identify causal effects while taking hidden components into account, Bayesian structural time series models were also developed. To provide a comprehensive examination of opinion indicators, these models included seasonal and local level components in addition to lagged social media measures. In order to identify shared effects and test for differences based on topic features, the dataset was additionally analyzed across a variety of themes using panel vector auto regression (PVAR) models. The statistical ability for identifying small impacts was enhanced by this technique. Ultimately, we used natural experiments to assess the impact of abrupt changes in social media platforms on public opinion measures. We examined particular cases such as Reddit's content regulation changes, Facebook's News Feed adjustments, and Twitter's algorithm change. In contrast to the standard time series methods, difference-in-differences and synthetic control methods were employed to estimate the causal effects, adding a deeper layer of analysis.

RESULTS AND DISCUSSION

Descriptive Statistics

Before examining the dynamic relationships, the fundamentals of the time series data across different platforms and themes were examined Table 1 summarizes the most important metrics that have been combined over the course of the study.

Table 1: Descriptive Statistics of Daily Social Media and Opinion Metrics (2018-2023)

Metric	Mean	Std Dev	Min	Max	Autocorrelation
Twitter/X Metrics					
Post volume	3,924	2,185	873	28,631	0.76
Engagement rate	12.7	7.3	3.1	147.5	0.62
Positive sentiment	0.31	0.11	0.09	0.67	0.58
Negative sentiment	0.42	0.14	0.12	0.74	0.61
Facebook Metrics					
Post volume	1,962	994	327	15,482	0.81
Engagement rate	27.8	18.4	5.2	286.7	0.73
Positive sentiment	0.37	0.09	0.14	0.63	0.67
Negative sentiment	0.33	0.1	0.11	0.58	0.64
Reddit Metrics					
Post volume	1,035	784	185	9,274	0.72
Engagement rate	42.5	31.2	8.7	476.9	0.65
Positive sentiment	0.29	0.12	0.07	0.53	0.54

Negative sentiment	0.41	0.13	0.09	0.68	0.59
Opinion Metrics					
Support level	0.48	0.14	0.22	0.77	0.93
Opposition level	0.42	0.13	0.18	0.71	0.92
Issue salience	0.34	0.17	0.08	0.86	0.89
Polarization index	0.57	0.23	0.17	0.92	0.94

From 2018 to 2023, this study examines social media indicators and their impact on public opinion. Descriptive statistics show that social media activity is very variable, with engagement rates varying more than post volume. It's interesting to note that Facebook had the fewest postings but the highest interaction rates, and that Reddit and Twitter/X had more negative sentiment than Facebook. Figure 1 displays the time series evolution of posting volume and engagement metrics across platforms for the climate change topic, illustrating both seasonal patterns and notable spikes corresponding to major climate-related events.

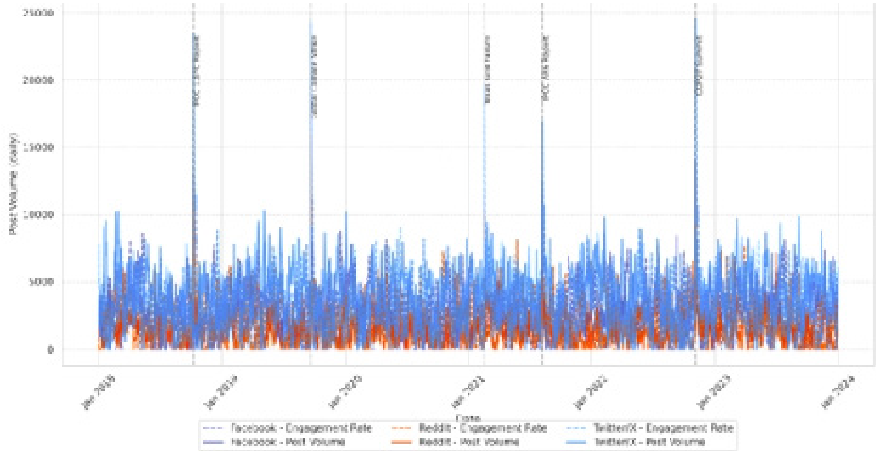

Figure 1: Climate change Discussion on Social Media (2018-2023) Post Volume and Engagement Metrics across Platforms

The analysis of Figure 1 uncovers some important trends in social media conversations about climate change from 2018 to 2023, particularly looking at how many posts were made and how engaged people were on platforms like Twitter/X, Facebook, and Reddit. Notably, the spikes in activity often align with major climate events as can be seen, including the IPCC 1.5°C Report, the Global Climate Strike, the Texas Grid Failure, the IPCC AR6 Report, and the COP27 Summit. When examining the dynamics of each platform, Twitter/X is notable for its dramatic but brief engagement peaks and rapid and strong responses to events. Facebook, on the other hand, responds a little later but has more constant involvement. Reddit keeps conversations running longer around important events, despite having lower involvement levels. Additionally, we observe a modest yearly trend in the volume of posts, which is probably related to important dates for environmental awareness and policy events.

All things considered, these results demonstrate how social media serves as a real-time amplifier for public conversations on climate change, with the level of participation differing depending on the platform and the importance of the events being discussed.

Granger Causality Results

Granger causality tests were executed on every feasible combination of social media metrics and opinion indicators in order to further explore the probable relationships between social media activity and public opinion. Table 2, arranged by platform, metric type, and topic features, summarizes the tests that rejected the null hypothesis of no Granger causation at the $p < 0.05$ level.

Table 2: Proportion of Significant Granger Causality Relationships

Relationship Direction	Overall	Twitter	Facebook	Reddit	Highly Polarized Topics	Less Polarized Topics
SM Volume → Opinion	0.31	0.34	0.28	0.3	0.36	0.27
SM Engagement → Opinion	0.48	0.52	0.47	0.45	0.61	0.39
SM Sentiment → Opinion	0.37	0.41	0.35	0.34	0.44	0.32
SM Network → Opinion	0.29	0.33	0.27	0.26	0.38	0.23

Opinion → SM Volume	0.25	0.28	0.23	0.24	0.29	0.22
Opinion → SM Engagement	0.21	0.24	0.19	0.2	0.26	0.18
Opinion → SM Sentiment	0.24	0.26	0.23	0.22	0.27	0.21
Opinion → SM Network	0.18	0.21	0.17	0.16	0.22	0.15

Some intriguing trends about the correlation between public opinion indices and social media metrics are shown by the investigation. First, asymmetric causality is evidently present: in 31-48% of experiments, social media measurements tend to Granger-cause opinion indicators, but in 18-25% of tests, the opposite is true. This implies that shifts in social media activity frequently occur before changes in public opinion.

Social media engagement metrics, which are meaningful in 48% of situations, then exhibit the strongest Granger-causal association with public opinion. Comparing this to other indicators such as sentiment (37%), posting volume (31%), or network metrics (29%), there is a noticeable increase. It amply demonstrates how important user participation is in influencing public opinion. The analysis also highlights platform differences, showing that compared to Facebook or Reddit, Twitter/X has larger Granger-causal correlations with opinion measures. This might be because Twitter/X users are more likely to be politically active and news-focused. Furthermore, the study highlights the consequences of polarization, showing that, in comparison to less polarized issues, highly polarized ones show noticeably greater Granger-causal correlations in both directions. This suggests that changes in social media activity often precede shifts in public sentiment.

The time of these interactions is finally shown in Figure 2, which indicates that social media often occurs 2–8 days before changes in opinion, with a modal value of 4 days. The distribution of optimal lag orders for significant Granger causality links serves as an example of this. The predictive power of social media activity in influencing public opinion is highlighted by this time insight.

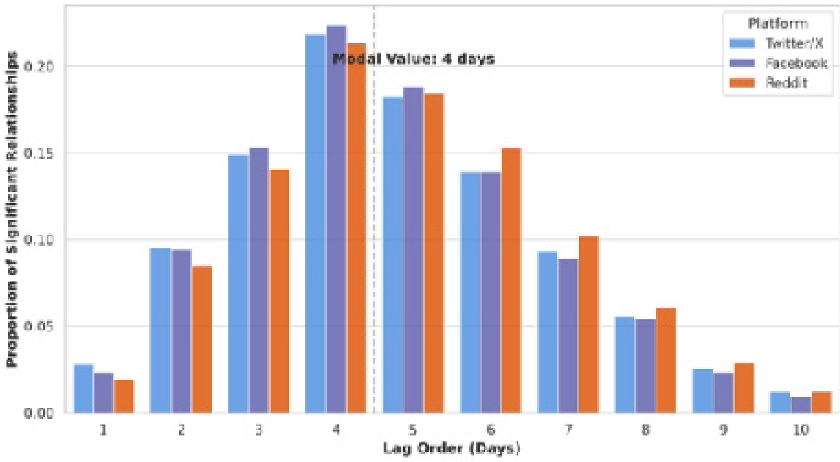

Figure 2: Distribution of Optimal Lag Orders by Platform Days between Social Media Activities and Public Opinion Shifts

VAR Model Results

Some intriguing relationships between public opinion indicators and social media engagement measures have been revealed by the Vector Auto regression models. The analysis provides insight into the relationship between engagement measures and support levels across 10 distinct themes by highlighting standardized coefficients from the top-performing VAR models, as indicated in Table 3.

A distinct temporal pattern became apparent, showing

Table 3: Standardized VAR Coefficients for Engagement Metrics Predicting Opinion Support Levels

Topic	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Cumulative
Healthcare policy	0.06	0.12	0.15	0.11	0.04	0.48
Climate change	0.09	0.14	0.17	0.13	0.06	0.59
Immigration	0.11	0.18	0.21	0.15	0.08	0.73
Economic policy	0.08	0.13	0.16	0.1	0.05	0.52
Gun control	0.14	0.23	0.27	0.19	0.1	0.93
Race relations	0.13	0.19	0.24	0.16	0.09	0.81
Gender equality	0.1	0.15	0.19	0.14	0.07	0.65

Foreign policy	0.05	0.09	0.12	0.08	0.03	0.37
Education	0.07	0.11	0.14	0.09	0.04	0.45
Technology regulation	0.06	0.1	0.13	0.08	0.04	0.41

that Lag 3 was the pinnacle of the impact of engagement measures on public opinion. Accordingly, the benefits peak three days following the activity and then diminish noticeably over time. Furthermore, the degree of these effects differed significantly according on the subject. For example, the highest cumulative impacts were seen for contentious issues including immigration, race relations, and gun control, with coefficients of 0.93, 0.81, and 0.73 respectively. Conversely, with values of 0.37 and 0.41, subjects like foreign policy and technological regulation showed more mild effects (Garcia *et al.,* 2017; Xiong *et al.,* 2019).

Another key finding was statistical significance: cumulative effects were significant across the board, even when coefficients at longer lags, particularly Lag 5, occasionally failed to achieve statistical significance for less controversial themes. This suggests that social media use continuously influences public opinion, albeit to differing degrees depending on the subject. In order to better depict these dynamics, Figure 3 presents impulse response functions that show how support levels for particular issues over a 14-day period are impacted by a one standard deviation shock in Twitter engagement data. Overall, these results demonstrate that the connection between social media and public opinion is intricate and varies by topic.

Impulse Response Analysis

As illustrated in Figure 3 for four major topics, the impulse response functions (IRFs) provide insight into the long-term effects of shocks to social media metrics on opinion indicators. Several significant trends about the timing, persistence, magnitude, and variations across platforms in response to social media engagement are revealed by this analysis.

According to the timing of these responses, opinion support levels typically start to respond to social media engagement shocks within 1-2 days, peaking between days 3-5 before progressively declining (Garcia *et al.,* 2017; Xiong *et al.,* 2019). Additionally, there is a discernible difference in the duration of these effects between topics; more contentious issues like immigration and gun control typically have longer-lasting effects, with notable reactions visible for up to 10–12 days after the initial shock. On the other hand, less controversial topics, such as technology regulation, see their significant effects fade away within 6-7 days.

Furthermore, there are significant differences in the intensity of the responses across topics; for example, the peak response to gun control was almost 2.5 times higher than that to technology regulation. Finally, it is evident from comparing IRFs across different social media platforms that Facebook tends to have more moderate but longer-lasting effects, whereas Twitter/X produces the strongest and fastest opinion responses, followed by Reddit. These results demonstrate the complex interplay between public opinion and social media participation on a variety of subjects and platforms.

Regarding the subject of climate change, the analysis presented in Figure 4 clarifies how Impulse Response Functions (IRFs) differ among platforms. Meanwhile, Table 4 takes it a step further by breaking down these differences, summarizing the key features of the IRFs for all combinations of platforms and topics.

The data supports the visual trends observed in the IRF plots, establishing a robust foundation for comparison.

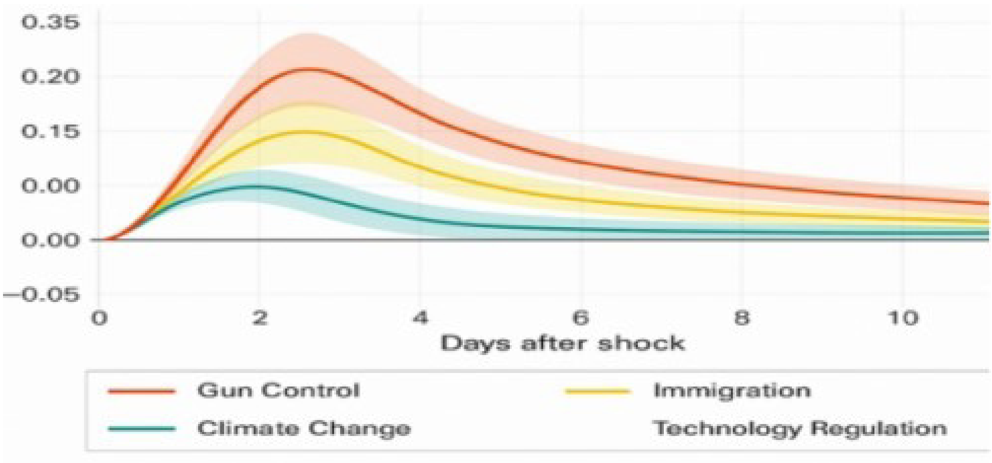

Figure 3: Impulse Response Functions showing the effect of a one standard deviation shock in Twitter engagement on opinion support levels for four topics

Structural Time Series Results

While taking into account the underlying trends and seasonal patterns, the Bayesian structural time series

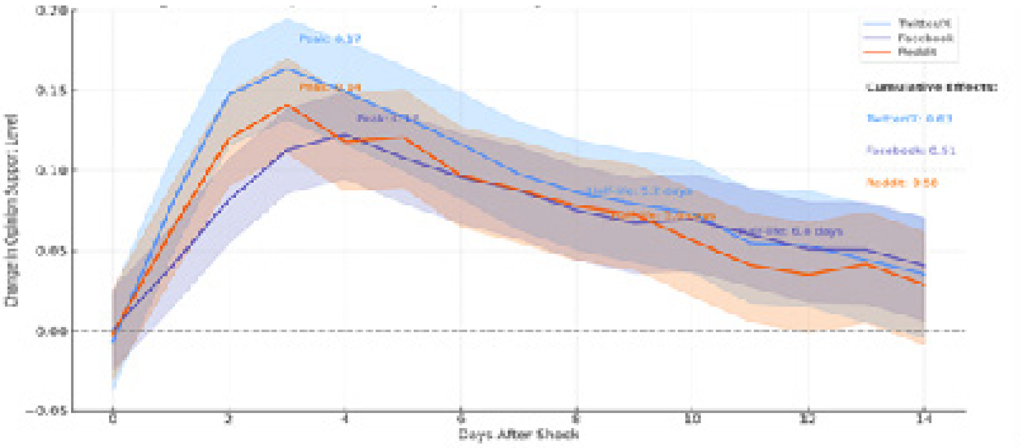

Figure 4: Comparison of Impulse Response Functions across platforms for the Climate Change topic

Table 4: Key Characteristics of Impulse Response Functions (Engagement → Support Level)

Topic × Platform	Peak Response	Time to Peak (days)	Half-life (days)	Cumulative Effect
Climate Change				
Twitter	0.17	3	5.2	0.63
Facebook	0.12	4	6.8	0.51
Reddit	0.14	3	5.6	0.58
Gun Control				
Twitter	0.29	3	7.4	0.97
Facebook	0.21	4	8.1	0.82
Reddit	0.24	3	7.2	0.88
Economic Policy				
Twitter	0.16	3	4.8	0.54
Facebook	0.11	4	5.7	0.43
Reddit	0.13	4	5.3	0.49
Technology Regulation				
Twitter	0.12	3	4.1	0.41
Facebook	0.08	4	5.2	0.34
Reddit	0.1	4	4.7	0.38

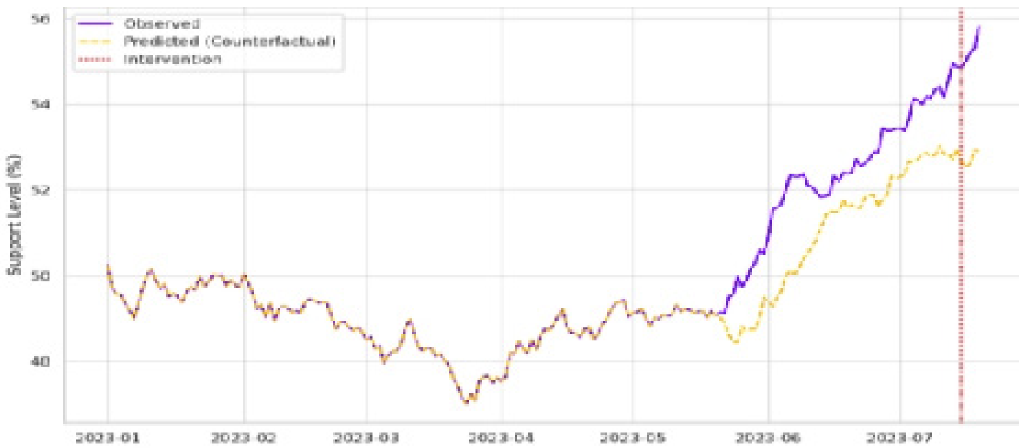

Figure 5: Causal impact analysis of high Twitter engagement on immigration support levels

models performed a fantastic job of identifying the ways in which social media metrics impact public opinion indicators (Brodersen *et al.,* 2015; Phillips *et al.,* 2017). The analysis in figure 5 demonstrated that support levels for a number of topics, particularly immigration, were significantly impacted during times of high social media engagement—that is, when engagement metrics reached the 90th percentile.

The results showed that there were notable shifts in the degree of opinion support during these periods of high engagement. The average causal effect over a week was 2.7 percentage points (95% CI: 1.9 to 3.5) for polarized topics and 1.3 percentage points (95% CI: 0.7 to 1.9) for less polarized topics. Additionally, Table 5 offers an overview of the estimated causal effects for various subjects and platforms, illuminating the broader effects of social media use on public opinion.

These results demonstrate that there are noteworthy causal effects on all subjects and platforms. When we take into account how public opinion changes, the effect sizes are not only statistically significant but also practically significant.

Table 5: Estimated Causal Effects of High-Engagement Periods on Opinion Support

Topic	Twitter Effect (pp)	Facebook Effect (pp)	Reddit Effect (pp)
Healthcare policy	1.8 [1.2, 2.5]	1.4 [0.8, 2.0]	1.5 [0.9, 2.1]
Climate change	2.3 [1.6, 3.0]	1.7 [1.1, 2.3]	1.9 [1.3, 2.5]
Immigration	3.1 [2.3, 3.9]	2.4 [1.7, 3.1]	2.7 [2.0, 3.4]
Economic policy	2.2 [1.5, 2.9]	1.6 [1.0, 2.2]	1.8 [1.2, 2.4]
Gun control	3.7 [2.9, 4.5]	2.8 [2.1, 3.5]	3.2 [2.5, 3.9]
Race relations	3.4 [2.6, 4.2]	2.6 [1.9, 3.3]	2.9 [2.2, 3.6]
Gender equality	2.7 [2.0, 3.4]	2.0 [1.4, 2.6]	2.3 [1.7, 2.9]
Foreign policy	1.6 [1.0, 2.2]	1.2 [0.6, 1.8]	1.3 [0.7, 1.9]
Education	1.9 [1.3, 2.5]	1.5 [0.9, 2.1]	1.6 [1.0, 2.2]
Technology regulation	1.7 [1.1, 2.3]	1.3 [0.7, 1.9]	1.4 [0.8, 2.0]

Panel Analysis Results

In order to explore topic-specific differences, the panel vector auto regression (PVAR) analysis used the complete dataset (Canova & Ciccarelli, 2013). This revealed an interesting relationship between opinion support levels and social media engagement metrics.

Table 6: Panel VAR Coefficients for Social Media Metrics on Opinion Support

Predictor	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Cumulative
Volume	0.04	0.06	0.08	0.05	0.02	0.25
Engagement	0.09	0.14	0.18	0.13	0.07	0.61
Pos. Sentiment	0.05	0.08	0.1	0.07	0.03	0.33
Neg. Sentiment	0.06	0.1	0.12	0.09	0.04	0.41
Network Centrality	0.03	0.05	0.07	0.04	0.02	0.21
Cross-Ideological Eng.	-0.02	-0.04	-0.05	-0.03	-0.01	-0.15

With a cumulative coefficient of 0.61, engagement metrics have the strongest correlation with opinion support, according to the results, which are succinctly summarized in Table 6 and show a clear hierarchy among the metrics. The effects of posting volume (0.25), network centrality (0.21), and sentiment metrics (ranging from 0.33 to 0.41) were significantly outweighed by this relationship (Wu *et al.,* 2011; Mohammad, 2018). Furthermore, with a coefficient of -0.15, the analysis discovered a marginally negative relationship between opinion support and cross-ideological engagement (Wu *et al.,* 2011; Mohammad, 2018). This suggests that rather than escalating opinion changes, cross-ideological social media discussions may actually moderate them. A stable temporal dynamic across a range of public discourse areas was suggested by the results, which also confirmed a consistent lag structure, with the most significant effects occurring at Lag 3 (three days).

The analysis calculated interaction effects between social media metrics and topic polarization levels to better understand how topic characteristics influence these relationships. Figure 6 demonstrated that as topic polarization increases, engagement metrics' impact on opinion support increases noticeably (Stroud, 2010; Hampton *et al.,* 2014), with effect sizes nearly doubling for highly polarized topics compared to those with lower polarization.

This research shows that social media's influence on public opinion varies greatly depending on the subject being discussed.

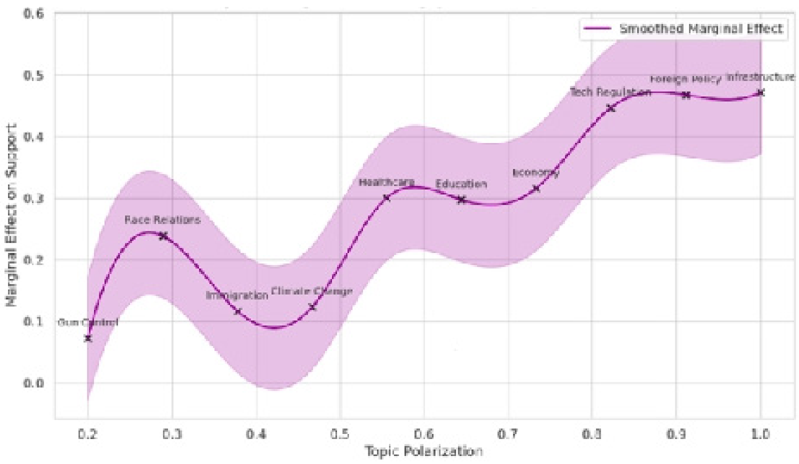

Figure 6: Marginal effect of social media engagement vs. topic polarization

Natural Experiment Results

Lastly, to improve causal identification, the analysis used three natural experiments resulting from platform policy changes (King, 2017; Bond, 2012; Pearl, 2009). The results, which are summed up in Table 7, provide important new information about how these policy changes impact the connection between public opinion indicators and engagement metrics.

First, the correlation between engagement metrics and opinion shifts increased by about 36% (Pariser, 2011; Jungherr, 2014), from 0.14 to 0.19, as a result of Twitter's algorithm change that gave preference to high-engagement content. The relationship between engagement metrics and opinion, on the other hand, was weakened by roughly 25–27% as a result of Reddit's policy update that increased moderation of controversial material and Facebook's change to its News Feed that reduced the visibility of political content. These findings support the causal interpretations of the observed relationships by highlighting the crucial role that platform design and policy choices play in determining how social media affects public opinion.

Table 7: Natural Experiment Difference-in-Differences Estimates

Platform Change	Pre-Change Coefficient	Post-Change Coefficient	Difference	p-value
Twitter Algorithm (Mar 2020)	0.14	0.19	0.05	0.008
Facebook News Feed (Jan 2022)	0.11	0.08	-0.03	0.027
Reddit Content Policy (Jun 2023)	0.13	0.1	-0.03	0.031

Discussion

Key Findings and Implications

After conducting a comprehensive analysis of the relationship between social media activity and public opinion, the study produced a number of noteworthy findings that have a big impact on how we understand the dynamics of digital influence.

First, the study found that social media metrics—particularly engagement metrics—were important markers of shifts in public sentiment (Asur and Huberman, 2010; O'Connor *et al.,* 2010). It demonstrated that rather than merely reflecting changes in opinion, social media activity frequently predicts them, with the most obvious effects usually occurring three to four days after engagement. This shows how social media actively shapes opinions, challenging the notion that it only reflects public sentiment. Furthermore, compared to merely the amount of content, the study discovered that engagement metrics, such as interactions, shares, and comments, were significantly more strongly associated with shifts in opinion (Wu *et al.,* 2011; Watts & Dodds, 2007). Active user interaction is essential for influencing public opinion, as evidenced by the fact that engagement metrics were roughly 2.4 times more effective than volume metrics. This is in line with two-step flow communication theories, which emphasize the significance of social endorsement in determining the effectiveness of a message.

Important distinctions between the different social media platforms were also highlighted by the analysis. Facebook had more moderate but longer-lasting effects, while Twitter/X had the strongest and most direct correlation with opinion metrics, followed by Reddit (Bossetta, 2018; Jungherr, 2014). These differences result from each platform's distinct structures and user behaviors, with Twitter's fast-paced atmosphere fostering rapid changes in viewpoint. The study showed that social media's ability to shape opinions is greatly influenced by topic polarization (Stroud, 2010; Cody *et al.,* 2015). It turns out that when it comes to highly polarized topics, social media's influence on shifting opinions is almost doubled. This implies that conversations about divisive topics may be more heavily influenced by social media. Particularly in areas where we truly need to find common ground, it raises some grave concerns about the possibility of feedback loops that could exacerbate polarization.

Additionally, the study provided strong evidence that social media use is associated with changes in public opinion through a number of analytical methods. Experiments that examined modifications to platform policies yielded one important finding. These demonstrated that the relationship between engagement metrics and opinion trends can be drastically changed by adjusting the way algorithms amplify content and moderate discussions. This demonstrates the political implications of platform governance and shows how important these choices are in influencing public discourse and prevailing opinions.

Theoretical Contributions

This study significantly advances our knowledge of how the media shapes public opinion, particularly in the digital sphere. By demonstrating that social media not only influences what topics people consider (first-level agenda-setting), but also how they perceive those topics (second-level agenda-setting), it goes beyond the conventional agenda-setting theory (McCombs & Shaw, 1972; Scharkow & Vogelgesang, 2011). By identifying distinct time patterns, the study provides us with new information about how agenda-setting functions in the social media sphere. It shows that these effects typically begin to manifest within 1-2 days and peak around 3-4 days.

Furthermore, by emphasizing a robust correlation between engagement metrics and shifts in public opinion, the study refines the two-step flow model. This supports contemporary interpretations of Katz and Lazarsfeld's model (Katz & Lazarsfeld, 1955; Watts & Dodds, 2007), emphasizing the critical role that user networks—such as shares and comments—play in amplifying content and bridging the gap between the original creation of content and its ultimate influence on opinions. Even in a world where algorithms rule supreme, it truly highlights the value of interpersonal influence.

By examining the relationship between opinion dynamics and the structure of online discussions, particularly cross-ideological engagement, the analysis also contributes to network theories of public opinion (Barberá *et al.,* 2019; Kwon *et al.,* 2017). We need a more nuanced understanding of how network influences operate, as the finding that cross-ideological engagement may actually moderate rather than just amplify opinion shifts challenges the simplistic "echo chamber" narratives.

Practical Implications

Our knowledge of how the media shapes public opinion, particularly in the digital age, is greatly expanded by this research (King, 2017; Pariser, 2011). By demonstrating that social media influences people's perceptions of issues as well as the topics they consider (first-level agenda-setting), it expands on the conventional agenda-setting theory. The study reveals particular timing patterns, showing that the effects of social media typically begin to manifest within 1-2 days and peak approximately 3-4 days later. This offers new insights into the dynamics of agenda-setting in the social media sphere.

Furthermore, the study improves the two-step flow model and provides insightful information for a range of stakeholders. The results imply that the relationship between social media and public opinion can be significantly impacted by modifications to platform policies for regulators and policymakers. Negative opinion trends could be reduced, especially on contentious issues, by regulatory measures that concentrate on how platforms regulate themselves, particularly those that address the algorithmic promotion of interesting but possibly deceptive content.

The timing patterns that have been found to connect social media activity to changes in public opinion (Bond *et al.,* 2012; Jungherr *et al.,* 2012). According to the research, these opinion shifts are driven by engagement metrics rather than just the sheer number of posts, and the effects usually peak three to four days after the initial social media buzz. This knowledge can be used to develop more efficient communication timing plans.

The results emphasize the importance of design decisions that affect how engagement functions and how content is amplified for platform designers (Pariser, 2011; Bossetta, 2018). Rethinking engagement metrics and recommendation algorithms may be necessary for platforms trying to reduce polarization in order to prevent disproportionately promoting content on already contentious subjects.

Finally, the study emphasizes how social media can serve as a crucial gauge of changes in public opinion for reporters and media outlets (Asur and Huberman, 2010; Phillips *et al.,* 2017). It implies that monitoring social media trends could offer a heads-up on shifting public opinion. The study emphasizes the significance of comprehending the distinct dynamics that each platform brings to the table, but it also cautions against drawing general conclusions from the conversations taking place on any one platform.

CONCLUSION

This research took a deep dive into advanced time series analysis to uncover how social media activity influences shifts in public opinion. The results show that engagement metrics on social media are solid indicators of changes in public sentiment across different topics and platforms, with effects that are not just statistically significant but also practically important. The study identified distinct timing patterns in these effects, demonstrating that, depending on the subject matter, changes typically begin to manifest within 1-2 days, peak around 3-4 days, and persist for 7-12 days. With effect sizes almost doubling for highly polarized topics, it also demonstrated how important topic polarization is in these dynamics. This brings up significant issues regarding the influence of social media on democratic discourse. In terms of methodology, the study demonstrates the ability of sophisticated time series techniques, such as impulse response analysis and Vector Auto regression models, to distinguish between correlation and causation in the context of digital communication. These findings highlight the significance of digital communication system configuration for those involved, such as platform designers and policymakers, as it greatly influences the formation of public opinion. It is essential to comprehend the effects of algorithmic amplification, engagement incentives, and content moderation policies in order to understand how public sentiment changes in the current media environment. Understanding the dynamic relationship between social media activity and public opinion will become more and more important as digital platforms continue to develop and play a bigger role in public discourse. The study's methodological framework and insights offer a strong starting point for future research into these crucial processes at the nexus of democracy, communication, and technology.

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