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Setting the Public Sentiment: Examining the Relationship between Social Media and News Sentiments

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Abstract: This study investigates whether news sentiment plays a role in setting social media sentiment to explore the dynamics of sentiment develop and diffusion within the public agenda. Based on the agenda-setting theory, this study analyzed the public and media sentiments towards the 2016 US election and the candidates using data from Twitter, CNN, and Fox News. Focusing on the Twitter messages created by the supporters of Hillary Clinton and Donald Trump, over 1.3 million Twitter messages were collected associated with the election, employing hashtags as indicators of support. The Granger causality test between social media and news sentiments revealed that there is a mutual influence between social media and news sentiments; CNN's overall sentiment was influenced by the sentiment of Hillary Clinton's supporters, whereas Trump supporters' sentiment was influenced by Fox News' negative sentiment. The results suggest that public sentiment is formed in response to public agenda and mass media, indicating that sentiment is a critical component in understanding public opinion. Implications for future studies and limitations are also discussed.

Keywords: sentiment analysis; social media; public opinion; agenda-setting; sentiment diffusion

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1. Introduction

Today, microblogging has become a common platform for expressing opinions, appraisals, attitudes, and emotions among people, and Twitter is now recognized as an important platform for political engagement [1]. As an electronic public sphere, social media often reflects newsworthy issues that attract people's attention and exhibits collective interests and attention [2]. Sentiment analysis of social media, a research method used to mine people's views and feelings, has become prominent in recent years as a tool to explore how people perceive current issues and monitor public opinion [3,4]. The current study analyzes public sentiment, assuming that those conversations and the emotional contents reflect public opinion, which provide information about public's dispositions [5]. More importantly, the transfer of emotional salience between social media and news is examined to investigate the dynamics of emotion formation and diffusion in public agenda and whether the sentiment of news influences the development of social media sentiment.

There is a growing interest in capturing public opinion by incorporating social media data as a proximate to self-reported public opinion surveys [6,7]. Given that social media is now an essential part of the public sphere, conversations about political issues in which people voluntarily engage online facilitate the detection of public opinion [8]. Increasingly, scholars are viewing social media as a new indicator of public salience reflecting current social behavior [9]. Sentiment analysis of social media posts in particular, is found to be useful because it can determine the emotional attitude of the author automatically [10]. Past research has shown that the sentiment of social media corresponds with ongoing political events as individuals utilize social media to express their thoughts and feelings, especially during political events [11,12].

The agenda-setting theory has evolved continuously since its initial Chapel Hill study in 1968 [13]. Such development has progressed from an emphasis on first-level agenda-setting effects, which focus on the objects of the agenda, to an exploration of second-level agenda-setting, concerning the attributes of the agenda [14]. According to Coleman and Wu [15], the emotional reactions triggered by affective aspects of a message play a role shaping the overall assessment of an object. As affective attributes and sentiments are as just as important as the cognitive level of transfer of an object, there is likely to be a relationship between the tone of the news and the public's emotional reactions [5]. Following this line of research, the current study aims to identify whether the sentiment of news media plays a role in setting the sentiment of social media, with the ultimate goal of gaining a deeper understanding of the development of public opinion by applying the agenda-setting theory. The current study explores the case of the 2016 Presidential election and examined the relationship between mainstream TV news, including Fox News and CNN, and Twitter sentiments on the two presidential candidates, Hillary Clinton and Donald Trump as social media provides an opportunity to assess the relationship between expressed sentiment by the public and political events [16].

1.1. Agenda-Setting Theory and Emotions

According to the agenda-setting theory, media have a significant role in influencing public opinion and the transfer of issue salience from media to the public agenda is a critical element in the formation public opinion [17,18]. Traditionally, public agenda has been measured in the form of public perceptions, mostly through opinion surveys, with researchers asking respondents to rank perceived issue importance [19]. The magnitude of agenda-setting effects is moderated by a variety of individual differences. One such moderator is the individual's cognitive involvement with an issue, specifically, each individual's perception of the issue's relevance [14,19]. The relevance hypothesis proposes that individuals depend on information from media to shape their political judgements when the information holds relevance [20]. In addition, studies found that emotional reactions to news influence issue salience, mediating agenda-setting effects. Emotions can increase relevance and people may recognize that an issue is important even if it lacks personal or social relevance to them [21].

According McCombs [22], agenda-setting effects on individuals depend on five personal motivations: civic duty, emotion, advocation, peer influence, and self-interest. Similarly, Miller [20] emphasized emotional relevance, an affective aspect of issues salience, suggesting that it increases the visibility of the issue for individuals. McCombs [22] demonstrated that the motivation for individuals to perceive an issue as significant can be attributed to emotional arousal. Empirical studies further confirmed that emotions indeed play a mediating role in agenda-setting, irrespective of the personal relevance of the issue [21]. For example, Young [23] argued that issues presented in the news were considered more important when they were perceived as fearful. Miller [20] found similar results, revealing that issues causing people to feel sad or fearful were viewed as nationally important.

Over the past decades, there has been scholarly interest in understanding the role of emotion in political behavior. The prevailing consensus is that media messages can elicit emotional responses, consequently influencing the cognitive processing of information and shaping public opinion [5]. News is a major source of political sentiment and has an impact as an important site for emotion production and management [24]. In particular, people tend to show a high level of sentiment in times of election when discussing their political views on social media, intensifying the influence of emotions [25]. Recent studies found that Twitter sentiments tend to follow political events and news coverage because social media enables people to express their opinions about the issues [26]. Therefore, this study attempts to identify whether social media sentiment plays a role in setting news media sentiment or vice versa, providing insights about the development and dissemination of emotion in public agenda.

1.2. Social Media and Opinion Mining

Public opinion is a collective aggregation of individual opinions on specific issues that pertain to a group of people, comprising mass moods, emotions, and assessments [27]. Emotion, which is generally characterized as psychological and physical reactions to external stimuli, encompass five constituent processes: an evaluation of the potential consequences of stimuli on one's goals, physiological changes in preparation for action, changes in cognitive processes to facilitate adaptation, an inclination towards a specific course of action, and the subjective experiential aspect of an emotions commonly referred to as "feeling" [28]. Emotions, which tend to last only a few minutes, are different from mood and affect, although these two are related concepts [29]. According to Massumi [30], affect refers to uncontained bodily intensities and emotions are "recognized affect, an identified intensity" (p. 61). The significance of affect in understanding human cognition and motivation processes is emphasized because of its distinct biological categories. Massumi [30] pointed out that emotions are social and affects are "prepersonal". Although some studies use affect and emotion interchangeably, these two terms are considered to be synonymous, encompassing both the relational and experiential aspects of intensity within individual bodies. For the purpose of this study, the term "sentiment" is used as a general reference to encompass affect or emotion.

Sentiment analysis is a computational linguistics technique which extracts and summarizes the opinions of a high volume of data to understand behaviors, trends, attitudes, and emotions from the subjective information [31]. Sentiment analysis has attracted academic attention for its use in understanding how the public perceives current affairs and an increasing number of studies have used social media sentiment to measure public opinion [2,32]. For instance, scholars have applied sentiment analysis to identify public's attitude towards the cryptocurrencies [33], climate change [4], Hong Kong Protest [34], global warming [35], and COVID19 [36,37]. Moreover, relatively high correlations were found between public opinion polls and social media posts in recent studies through automated text analysis, revealing large-scale trends [38]. For example, Lindsay [39] found correlations between Facebook posts and opinion polls conducted during the US presidential election, while O'Connor et al. [40] identified a positive association between Obama's approval rate and Twitter sentiments. Moreover, semantic analysis of Twitter predicted the outcomes of the 2010 UK election [41] and the 2011 Irish general election [42].

Recent research showed that social media is increasingly reflecting online issue salience. To the extent that Twitter is widely used and evenly represents demographic groups of American audience among the popular social media platforms, it is particularly a good source of online public opinion [43,44]. For example, Marchetti and Ceccobelli [45] demonstrated that online discussions about politics on Twitter affected public agenda during the 2014 Italian election by analyzing hashtags and keywords. In their 2018 study, Feezell [43] found that political information on Facebook influenced public agenda and Yang and Sun [44] showed media agenda corresponded with the social media agenda set by the individual opinion leaders on Paris attack. Feezell [43] further emphasized that social media, when the information comes from credible sources, might increase issue salience to a greater degree than if they were impacting a greater degree compared to when they are disseminated through mass media. In this context, Takeshita [46] contended that the rise of new media reshaped the agenda-setting process because the consensus-building of traditional media has decreased, while losing their ability to establish a "common public agenda" (p. 286).

As media and its sentiment influence the way people process information and shape public opinion, the sentiment of social media is also likely to be affected by news. Murthy and Petto [47] examined the relationship between the sentiments of elite newspapers and Twitter during the 2012 Republican Primary, although no substantive relationship was found. While studies on the empirical analysis of the relationship between the news and Twitter sentiments are limited, previous research on financial news provides some insights. Scholars found that both the news headlines about recession and the tone of economic news were significant predictors of consumer sentiment [48] and news sentiment was influenced by social media for financial news [49]. The current study extends the previous findings related to the role of emotion in the transfer of issue salience between news and social media by applying agenda-setting theory. As affective attributes and sentiments are as just as important as the cognitive level of transfer of an object, there is likely to be a relationship between the tone of the news and the public's emotional reactions [5].

Coleman and Wu's [15] analysis of the affective influence of visual information available on television introduced the concept of affective agenda-setting, suggesting that news media have agenda-setting effects on the audience emotions. Researchers have described affective characteristics as the components of a message that generate emotional reactions in an audience, such as the tone of the message. Second-level agenda-setting states that the emotional reactions triggered by affective aspects of a message play a role in shaping the overall assessment of an object [50]. Lopez- Escobar et al. [51] found a positive relationship between the affective attributes highlighted in the media and the ones emphasized by the general public. Similarly, people's evaluation of issue importance was influenced by the tone of the media coverage [52]. In their study, Coleman and Wu [15] demonstrated a positive association between the public sentiment towards a presidential candidate and the tone of media coverage about the candidate, concluding that a transfer of affective agenda from media to the public was found.

2. Research Question

This study attempts to identify whether social media sentiment plays a role in setting news media sentiment or vice versa, providing insights about the development and dissemination of emotion in the public agenda. Given that the affective attributes and sentiments are as important as the cognitive elements in the transfer of salience in the agenda-setting process [5], the current study extends the previous findings related to the role of emotion in the transfer of issue salience between news and social media. The current study explores the case of the 2016 Presidential election and examines the relationship between mainstream TV news, including Fox News and CNN, and Twitter sentiments on the two presidential candidates, Hillary Clinton and Donald Trump through the execution of a large-scale automated content analysis of Twitter messages and news coverage. As social media sentiment tends to correspond with news media, it is assumed that public sentiment is set around the issue that is talked about in the media and that emotional salience is transmitted via news and public discussion. Thus, the following research question was suggested:

R1. *Does social media sentiment set the news sentiment?*

3. Methods

The current study explored the case of the 2016 Presidential election and examined the relationship between mainstream TV news, including Fox News and CNN, and Twitter sentiments on the two presidential candidates, Hillary Clinton and Donald Trump. Sentiment analysis was used to measure and investigate sentiment salience, which is the frequency of sentiment words found in Twitter messages and news coverage.

3.1. Data Collection

3.1.1. Twitter Data

Twitter messages were collected through the Twitter API (Application Programming Interface) that included specific hashtags (#) every day. Hashtags are widely used in social media to mark messages on a specific topic or event, thereby stimulating group discussions [53,54]. The limit of search tweets is up to 18,000 for a single query, which may span as long as ten days or as little as a few minutes. Twitter messages of Hillary Clinton's supporters with the hashtag *#imwithher* were collected at 10 AM and 10 PM Pacific Time, and those of Donald Trump supporters with the hashtag *#trump2016* were collected at 11 AM and 11 PM Pacific Time. Both hashtags were extensively used by the candidates and their supporters during the election. Here, only English tweets have been taken into consideration and a total of 687,534 and 616,071 tweets were collected from of Hillary Clinton and Donald Trump supporters, respectively. For example, "More hate and racism from the Trump trolls. #ImWithHer" is a negative tweet in terms of sentiment by a Hillary Clinton's supporter and "Regardless of what your opinions may be, I believe it is time for a change. I believe it is time to MAKE AMERICA GREAT #trump2016" is an example of a positive tweet created by a Donald Trump's supporter.

3.1.2. News Data

The news articles used in this analysis were obtained from the Lexis-Nexis database and include only those articles containing issue-relevant keywords. The sample of news coverage consisted of news programs from cable news networks CNN and Fox News for the time period from 24 September 2016 to 7 November 2016. Television news was chosen considering the purpose of the current study, as it is more emotional than print news and is more strongly related to the audience's emotional responses [55]. In addition, research has consistently demonstrated that liberals and Democrats prefer CNN while conservatives and Republicans prefer Fox News [56]. Studies also show that American audiences get most of its national and international news from cable news channels during the elections [57]. Full-text transcripts of the news were accessed via the Nexis-Lexis database using the search terms "Trump election" and "Hillary election". A broad term was used to ensure that all relevant segments would be included in the data [58]. Stories that were not primarily related to the election were excluded to increase precision. A total of 1365 and 273 stories were collected from CNN and Fox News, respectively. For example, Fox News reported on 31 October 2016 "the reason she was giving it back had nothing to do with this because it hadn't happened yet. She's giving it back because you get closer to the end and the republicans were starting to come home for Donald Trump. They were sucking it up, and the resistant republicans were saying I hate her too much to vote for her". This is an example of negative news coverage of Hillary Clinton in terms of sentiment.

3.2. Data Analysis

3.2.1. Sentiment Analysis

Sentiment analysis is a computational linguistics technique which helps extract and summarize the opinions of a high volume of data to understand behaviors, trends, attitudes, and emotions from the subjective information [31]. Also known as opinion mining, the focus of sentiment analysis is to extract sentiment information, which reflects an individuals' perspective on a given topic [59]. Using the Linguistic Inquiry and Word Count (LIWC) affect dictionaries, which consist of discrete emotion categories, the current study analyzed Twitter and news media sentiments [60]. LIWC (2015) is a lexicon-based sentiment analysis software that categorizes and calculates the percentage of total words present in a given text. Widely employed in the fields of psychology and linguistics, LIWC helps identify psychological cues such as judgments, emotional states, thought processes, and deceptions [61]. With a total of 85 categories, the LIWC dictionary consists of four main dimensions: psychological constructs, personal concerns, informal language markers, and punctuation. The psychological construct category includes subcategories such as affect, cognition, biological processes, and drives. The dimension of affect is composed of positive emotions (e.g., nice, love, sweet), negative emotions, and three specific emotions of anxiety (e.g., worry and fearful), anger (hate, kill, and annoyance), and sadness (crying and grief).

Figure 1 shows the five emotions along with their percentages of the total words in the data. Positive emotions were most prominent among Hillary supporters' tweets (M = 2.08, SD = 0.48), CNN (M = 2.47, SD = 0.23), and Fox News (M = 2.60, SD = 0.23). As shown in Figure 2, Trump supporters' tweets showed similar percentages of negative (M = 1.97, SD = 0.47) and positive emotions (M = 1.47, SD = 0.40).

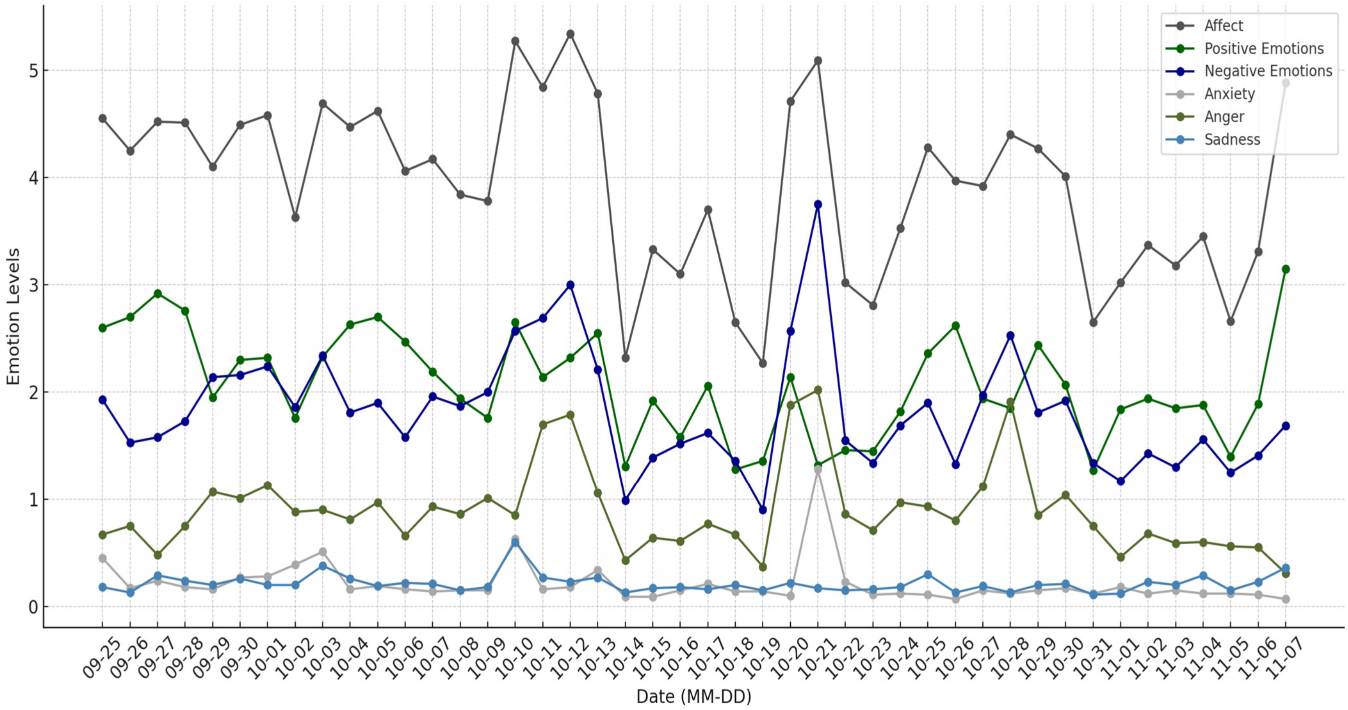

Figure 1. Time-series of Hillary supporters' negative and positive sentiment words by day.

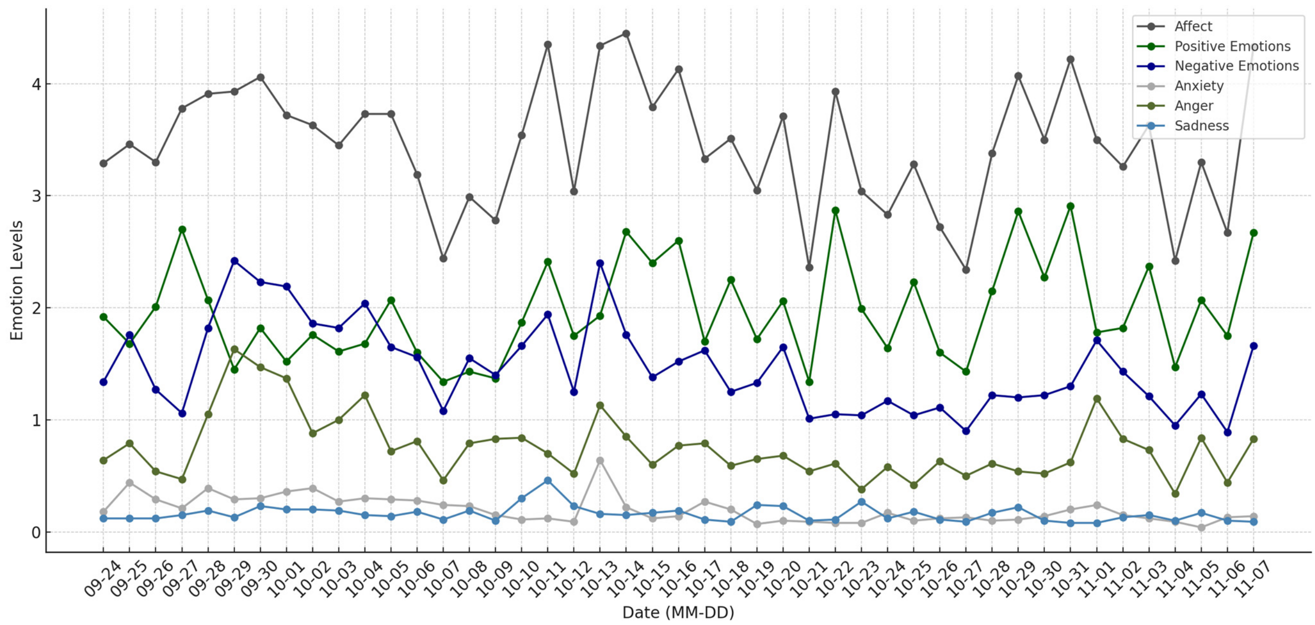

Figure 2. Time-series of Trump supporters' negative and positive sentiment words by day.

3.2.2. Granger Causality Test

Widely used in agenda-setting research, time-series analysis determines causal relationships [62]. The Granger causality test, which is one of several tests available in time-series analysis, enables the prediction of media agenda by considering past values of its agenda as well as those of other media types. It is suggested that it can yield more accurate results compared to other methods of time-series analysis [63]. The Granger causality test determines the direction of statistical causation between two time-series variables by examining whether a "measure x is said to Granger cause a measure y", when y can be more accurately predicted using the past values of x and y together than the past values of y alone [64]. Based on agenda-setting theory, this study compares media sentiment to news media sentiment. Applying Granger causality analysis permits predictions of sentiment as it reveals the direction of statistical causation between two time-series variables [65].

4. Results

4.1. Correlation Test

Table 1 shows the bivariate correlations between the sentiment measures of Twitter and news coverage. Overall, the negative emotions in both Twitter discussions were closely related to the emotions in news coverage, while positive emotions in Trump supporters' Twitter discussion negatively correlated with the emotions in the Fox News coverage of Trump. There was a significant correlation between negative emotions in Hillary supporters' Twitter discussion and negative emotions ($r = 0.29$, $p = 0.057$), anxiety ($r = 0.33$, $p < 0.05$) and positive emotions (r = 0.31, $p < 0.05$) in the CNN coverage of Hillary. Anxiety in Hillary supporters' Twitter discussion significantly correlated to affect ($r = 0.42$, $p < 0.05$), positive emotions ($r = 0.29$, $p < 0.05$), negative emotions ($r = 0.33$, $p < 0.05$), anxiety ($r = 0.37$, $p < 0.05$), and sadness ($r = 0.31$, $p < 0.05$) in the CNN coverage of Hillary. A positive correlation was found between anger in Hillary supporters' Twitter discussion between affect ($r = 0.35$, $p < 0.05$) and positive emotions ($r = 0.31$, $p < 0.05$) in the CNN portrayal of Hillary. Sadness in Twitter discussion was positively correlated to anxiety in the CNN coverage of Hillary ($r = 0.30$, $p < 0.05$).

Table 1. Bivariate correlations between twitter and news sentiments.

	1	2	3	4	5	6	7	8
1. Positive Emotion_Hillary	1							
2. Positve Emotion_Trump	−0.04	1						
3. Positive Emotion_CNN	0.08	−0.09	1					
4. Positive Emotion_Fox	0.11	0.10	0.67 **	1				
5. Negative Emotion_Hillary	0.19	−0.30 *	0.32	0.07	1			
6. Negative Emotion_Trump	0.29 #	−0.12	−0.10	−0.06	0.19	1		
7. Negative Emotion_CNN	0.03	−0.02	0.07	0.08	0.29 ##	0.34 *	1	
8. Negative Emotion_Fox	0.22	−0.33 *	0.01	0.00	0.27	0.46 **	0.48 **	1

* $p < 0.05$; ** $p < 0.01$; # $p = 0.053$; ## $p = 0.057$.

There was a significant correlation between negative emotions in Trump supporters' Twitter discussion and negative emotions ($r = 0.46$, $p < 0.05$) and anger ($r = 0.50$, $p < 0.001$) in the Fox News coverage of Trump. Anger in Trump supporters' Twitter discussion correlated with negative emotions ($r = 0.40$, $p < 0.05$), anger ($r = 0.27$, $p = 0.068$), and sadness in the Fox News coverage. Anxiety in Twitter on Trump was significantly correlated to negative emotions ($r = 0.44$, $p < 0.05$), anxiety ($r = 0.28$, $p = 0.058$), and anger ($r = 0.44$, $p < 0.05$) in the Fox News coverage of Trump. There was a negative correlation between positive emotions in Trump supporters' Twitter discussion and negative emotions ($r = -0.33$, $p < 0.05$) and anger ($r = -0.28$, $p = 0.064$) in the Fox News coverage of Trump.

4.2. Granger Causality Test

The Granger causality test results showed that there was a significant relationship between the Twitter sentiment and news media sentiments. Tables 2 and 3 summarize the results of the Granger causality test between Twitter and CNN sentiments. As shown in Table 2, emotions in Hillary supporters' Tweets Granger caused emotions in CNN rather than following them. Positive emotions in Hillary supporters' Tweets Granger caused positive emotions in CNN for lag 2 ($\beta = 6.23$, $p < 0.01$), 3 ($\beta = 5.21$, $p < 0.01$), 4 ($\beta = 3.91$, $p < 0.05$), 5 ($\beta = 3.04$, $p < 0.05$), 6 ($\beta = 2.44$, $p = 0.052$), 7 ($\beta = 2.51$, $p < 0.05$), and 8 ($\beta = 2.55$, $p < 0.05$). Anger in Hillary supporters' Twitter discussion Granger caused anger in the CNN coverage of Hillary for lag 1 ($\beta = 3.91$, $p = 0.054$), lag 2 ($\beta = 3.75$, $p < 0.05$), and 4 ($\beta = 3.92$, $p < 0.05$). On the contrary, Fox News affected the sentiments of Trump supporters. As indicated in Tables 4 and 5, negative emotions in the Fox News coverage of

Trump Granger caused negative emotions in Trump supporters' Tweets ($\beta = 6.52$, $p < 0.05$) for lag 1. Consistently, Fox News Granger caused anger ($\beta = 4.48$, $p < 0.05$) and anxiety ($\beta = 2.58$, $p < 0.05$) for lag 1 and 5, respectively. Additional analyses revealed that sadness in Fox News Granger caused anger in Trump supporters' Tweets for lag 1 ($\beta = 7.6$, $p < 0.01$), 2 ($\beta = 4.87$, $p < 0.05$), and 3 ($\beta = 4.02$, $p < 0.05$). However, Twitter did not Granger cause Fox News sentiment (see Table 5).

Table 2. Hillary supporters and news Granger causality Test—twitter to CNN.

Time-Lag	Positive Emotion	Negative Emotion	Anxiety	Anger	Sadness
1	0.13	3.54	0.134	3.92 ##	1.05
2	6.23 **	1.65	0.46	3.75 *	0.51
3	5.21 **	1.09	0.42	2.48	0.4
4	3.91 *	1.6	0.42	3.92 *	0.36
5	3.04 *	1.45	0.32	2.31	0.27
6	2.44 #	1.33	0.24	1.7	0.25
7	2.51 *	1.44	0.19	1.44	0.69
8	2.55 *	1.80	0.19	1.38	0.84

* $p < 0.05$; ** $p < 0.01$; # $p = 0.052$; ## $p = 0.055$.

Table 3. Hillary supporters and news Granger causality test—CNN to Twitter.

Time-Lag	Positive Emotion	Negative Emotion	Anxiety	Anger	Sadness
1	0.00	0.07	0.18	0.02	0.87
2	0.03	1.65	0.57	0.45	0.51
3	0.34	1.09	0.33	0.26	0.34
4	0.46	1.6	0.32	0.15	0.26
5	0.55	1.45	0.25	0.49	0.41
6	0.06	1.33	0.26	0.79	0.58
7	0.51	1.44	0.23	0.95	0.81
8	1.04	0.78	1.26	0.77	1.57

Table 4. Trump supporters and news Granger causality test—Twitter to Fox News.

Time-Lag	Positive Emotion	Negative Emotion	Anxiety	Anger	Sadness
1	1.42	0.83	0.3	0.01	0.82
2	0.75	0.39	0.14	0.26	1.75
3	0.40	1.18	1.87	0.80	2.48
4	0.48	0.95	1.07	1.5	1.77
5	0.70	0.8	0.78	2.01	1.48
6	0.52	0.4	1.4	1.37	1.2
7	0.81	0.63	1.04	1.5	0.85
8	0.65	0.71	1.26	1.78	0.77

Table 5. Trump supporters and news Granger causality test—Fox News to Twitter.

Time-Lag	Positive Emotion	Negative Emotion	Anxiety	Anger	Sadness
1	0.46	6.52 *	0.90	4.82 *	0.50
2	0.19	2.8	0.18	2.71	0.52
3	0.15	2.22	0.82	1.68	1.46
4	0.29	2.12	0.84	1.90	1.12
5	0.35	2.11	2.58 *	2.04	0.95
6	0.31	1.50	2.06	0.68	0.69
7	0.26	1.39	1.88	0.97	0.46
8	0.18	1.81	2.04	0.64	1.7

* $p < 0.05$.

5. Discussion and Conclusions

The main purpose of this study was to identify whether news sentiment plays a role in setting social media sentiment or vice versa. By applying agenda-setting theory, the current study extends the previous findings related to the role of emotion in the transfer of issue salience between news and social media. The results show that the relationship between social media and news sentiments depends on political affiliation. Hillary supporters' social media sentiment influenced news media sentiment while Trump supporters were influenced by right-leaning media during the 2016 presidential election. In particular, CNN picked up on social media's positive sentiments about Hillary Clinton's campaign whereas Trump supports' negative sentiment was influenced by Fox News sentiment. The results also suggest that the sentiments of news and the emotional reactions of the public are likely to be related.

Recent research on Trump supporters during the 2016 election indicates that anxiety and anger played a substantial role in shaping support for Donald Trump. Trump was able to attract his supporters by using emotional appeals to fear of minorities and foreigners, implying that they pose a threat to their safety and economic security [66]. The findings of the current study suggest that the negative tone of the news reports about Donald Trump and the election caused anger among Trump supporters, which later developed into anxiety, although Trump supporters' tweets showed similar percentages of negative and positive emotions overall. Given that anxiety is often associated with powerlessness and inability to manage perceived threats [67], it is likely that Fox News coverage about the election influenced Trump supporters to view political opponents as a threat, leading to social, economic, and cultural anxieties. As a result, the effects of emotional appeals by Trump were likely reinforced by right-leaning mainstream news outlets.

In the agenda-setting theory research, the extent to which an issue remains salient is a substantial question and the selection of time-lag is crucial because it determines the time-varying causal effects [68]. Compared to past agenda-setting studies, recent findings on social media show shorter time-lags, typically ranging from 1 to 7 days [8]. For instance, early research investigating agenda-setting effects within online discussion boards suggested a time-lag ranging from 1 to 7 days between mainstream news and online discussion boards [69]. Similarly, the current study revealed nearly immediate agenda-setting effects with the time-lag varying from 1 to 8 days. The relatively short time-lag indicates Twitter's instantaneous influence on information diffusion and the limited duration of attention devoted to issues during the presidential election. The time-lag between Fox News and Trump supporters' Tweets indicates that negative sentiment is short-lived because new issues that trigger negative emotions need to be addressed as the influence of Fox News sentiment dissipated after day 1 but reinstates on day 5.

The current study used publicly available online data to perform sentiment analysis which reduced the costs, efforts, and time required for large-scale public surveys and questionnaires [70,71]. In agenda-setting research, significant efforts have been made to establish the relationship between news media and public agenda through public opinion surveys asking respondents to list the most important problem our country is facing today. These surveys assess respondents' perceived issue salience using self-reported data based on free recall [72]. The current study examined the emotional content of public opinion by applying agenda-setting theory and demonstrated that public and media sentiments have mutual influence. Given that interpersonal discussions on political issues play a critical role in the public sphere, social media has been used as an important source of opinion mining, detecting public opinion [8]. The results of this study suggest that the sentiment analysis of social media not only allows exploring how people react to a specific event or candidate during the presidential election, but also reflects the influence of news media on public opinion. Thus, social media sentiments can be used as an index of public salience, enabling real-time analysis of changes in public opinion [73].

The focus of this study is to extend the previous research on whether there is a meaningful relationship between social media and news media sentiments, assuming that Twitter broadens public debate. In addition to its growing role in political discussion, Twitter is suggested to reflect collective emotions, potentially enabling prediction of political opinions and preferences. In his book, Murthy [74] stated that Twitter has the potential to facilitate our understanding of others, while expanding our knowledge domains. It connects us to a worldwide community and allows quick access to information and political participation. Papacharissi [75] suggested affective public, a new landscape replacing the old public sphere, where networked users interact around the news. Consistently, the current study shows that Twitter also plays an important role in shaping public and media agenda and that high volume of affective news was created in reaction to political events, reflecting users' subjective experiences and interpretations of those events.

Although the present study demonstrated the transfer of sentiments between news and social media, it is necessary to acknowledge and address limitations. For the purpose of this study, public sentiments towards two candidates during the 2016 US election was analyzed. Given that political social media messages tend to exhibit a high level of sentiment and the controversial nature of political discourse [25], it is likely that the influence of social media sentiment on news sentiment strengthened during the active political events, such as elections. Thus, it is important to exercise caution when generalizing this temporal relationship to other contexts and future research should consider examining other issues or events, such as economic and international issues.

It should be noted that Twitter does not represent social media platforms. Although Twitter may be an appropriate choice in some cases, such as political issues, it is important to examine more than one platform because there are other websites competing with or replacing Twitter, particularly among younger generations. There is a generation gap in the usage of social media platforms [76]. According to recent studies, about 42% of US adults aged 18–29 use Twitter but only 7% of US adults aged 65 and above are Twitter users [77]. Moreover, Park et al. [78] emphasized that Facebook and Twitter messages are different in terms of emotional appeals especially during the election, such that Facebook showed more positive sentiment compared to Twitter. Subsequent studies may expand this study to include a wider range of social media platforms to examine the relationship between news sentiment and social media sentiments.

The question regarding the extent to which news media contribute to social media sentiment is significant because emotions are not merely personal expressions but rather shaped by cultural discourses and guided by social rules [79]. This study intended to test the theoretical proposition by exploring whether the sentiments of news set the sentiment of social media, as a form of agenda-setting. Sentiment analysis of social media posts can be useful as it can determine the emotional attitude of the author. The current study revealed that there is a mutual influence between social media and news sentiments and that public sentiment is formed in response to the public agenda and mass media, suggesting that sentiment is a critical component in understanding public opinion.

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