THE NETWORKED INTERMEDIA AGENDA SETTING OF THE "BLACK LIVES MATTER" MOVEMENT BETWEEN NEWSPAPERS AND TWITTER: A MIXED-METHOD STUDY

By

YAN SU

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The Faculty of Washington State University:

The members of the Committee appointed to examine the dissertation of YAN SU find it satisfactory and recommend that it be accepted.

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It is early March of 2021 in Pullman, USA, as I write these words to conclude my dissertation. I feel a bit surreal to humbly present this manuscript as an outcome of my four years Ph.D. at the Murrow College of Communication, Washington State University.

This manuscript was mainly drafted in my small studio in Pullman, Washington during the past year. The unprecedented pandemic has made my studio a real "reclusive den." During this period of time, a month seemed like a day. I was a little anxious about this seemingly endless reclusive life at first, but from the small window of my studio I had the privilege to a bird's-eye view of a platanus tree, which has been patiently demonstrating to me the eloquence of the vicissitude with the change of its leaves. This small window has become a prism through which I switch, and ponder over the nexus, between the "changed" and the "unchanged."

A decade ago, in my home country where the gleam of idealism was still lingering, I, as a journalism-major undergrad, regarded becoming a journalist as a lifelong mission. However, when I gradually found that almost no single journalist could really get rid of the shackle of ideology and boundaries of criticism, I became aware that working for the news industry would not help me realize my ultimate value. Just when I was at a loss for the future, I saw a Chinese cultural scholar said, in a TV interview, that if a river were his research object, he would prefer to observe and record the riverbed, rather than the muds and sands. To me, a scholar is the one that humbly documents and analyzes what the riverbed looks like after the mudded water has flown down, rather than the one chasing a raging torrent. It was exactly through these observations,

deliberations and self-conversations that motivated me to resolutely embark on the road of academic research. Today, with years of academic training as a solid preparation, I seem to have the potential to formally embark on this path as a young scholar.

But it was not until these years that I realized that without the unconditional and silent support of my parents, I could hardly take this crucial step in my life. I used to attribute all my progresses and accomplishments to my own cleverness and hard work, feeling complacent. I have been grateful for the gift that fate has given me, the era I was born and raised, passersby who have praised me, and even strangers who have encouraged me in a few words, but I have rarely thought of thanking my parents, who have given me all they had and supported me regardless of what decisions I made. I would like to take this opportunity to thank my parents for their unconditional love and support. They are my anchors and stars, and they always will be.

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I dedicate this dissertation to my parents, my grandpa, and Jun.

THE NETWORKED INTERMEDIA AGENDA SETTING OF THE "BLACK LIVES MATTER" MOVEMENT BETWEEN NEWSPAPERS AND TWITTER: A MIXED-METHOD STUDY

Abstract

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The emergence of social media has altered the ways in which ordinary people obtain information and perceive the world. However, mixed results have been generated regarding whether or not traditional, elite media still have the significant influence in shaping what people discuss and how they discuss. Scholars have called for more attempts to address the who-leads-whom debate in various contexts. Using the perspective of network intermedia agenda-setting, this dissertation has three goals. (1) This dissertation investigates the ways in which the U.S. mainstream newspapers and Twitter set network agendas for the BLM movement. (2) This dissertation further explores how the network agendas of both platforms interact with each other over time. In other words, this dissertation strives to understand which platform – newspapers or Twitter – is more powerful in setting agenda for its counterpart, and at which level. (3) Upon drawing an overall conclusion based on the data analysis, this dissertation strives to further understand Twitter's impact on journalists' work routines, published works, as well as today's journalistic norms, through interviewing with frontline journalists.

Through analyzing a full sample of 4,189 newspaper articles and over 1.23 million tweets about the BLM movement, findings showed that newspapers and Twitter both placed saliencies to the substantive attributes such as police and policing, violence, systemic racism, and demonstrations. However, newspapers depicted these attributes using an overall supportive tone while Twitter users used a largely condemning tone. Further, both unidirectional and reciprocal effects have emerged between the newspapers and Twitter for the substantive attribute agendas, while newspapers showed an overall stronger power than Twitter. No effect was observed for affective attributes. When it comes to each substantive attribute combined with a specific affective attribute, the intermedia agenda-setting effects have shrunk significantly. In terms of the bundled substantive attribute agendas (i.e., the ways in which both media interconnected different substantive attributes as a network-like agenda), both platforms showed greater impacts on its counterpart, whereas the newspapers were more influential than vice versa. Lastly, null effect emerged when it comes to the combination of bundled substantive attributes and affective attributes. Implications were discussed.

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CHAPTER ONE

INTRODUCTION

> [W]here there is power, there is counterpower, enacting the interests and values of those in subordinate positions in the social organization. The shape of the institutions and organizations that construct human action depend on the specific interaction between power and counterpower. Power is multidimensional, and it is constructed around multidimensional networks programmed in each domain of human activity according to the interests and values of empowered actors.
>
> --- Manuel Castells (2011, p. 773-774)

Castells (2009) stressed, in his book *Communication Power*, that in contemporary society, the fundamental source of power and counterpower lies in "social networks" and "social networks of social networks that make use of global digital communication networks" (Castells, 2009; 2011; Fuchs, 2009, p. 94). To be specific, culture, organization, and technology of communication in a networked society are the bases upon which communications are operated, which, in turn, mediates the construction of power relationships in the given society (Castells, 2013). Today's society is, for sure, a network society, where the communication of interconnected and networked digital information can cause and facilitate political, cultural, and economic changes (Castells, 2007). The idea stems from Martin's (1978) conceptualization of "the wired society," in which different social actors are connected by mass- and telecommunication networks. In this highly networked society, the network-making power is "the paramount form of power"

(Castells, 2013, p. 47).

As Castells (2011) has specified, network-making power refers to the power to “set up and program a network,” which is oftentimes owned by media conglomerates that possess “the financial, legal, institutional, and technological means to organize and operate mass communication networks” (p. 781). However, the near-monopoly position and unparalleled capacity of media giants have evidently been weakened with the rise of social media (Chen, Su & Chen, 2019). With the popularization of digital technology and the rapid increase of the penetration of intellectual devices, public opinions on social media have become so omnipresent and powerful that any traditional power body can no longer ignore. Scholars are clearly cognizant of the duality of the social ramifications of the emerging power of social media. On the one hand, pundits and scholars are optimistic about the network-making power of the social media in visualizing the powerless and posing challenges to some crystalized societal norms (Jost et al., 2018; Loader & Mercea, 2011), which is reflected in, for instance, the umbrella movements and the anti-Extradition Bill movement in Hong Kong and the Black Lives Matter movements in the United States. On the other hand, some scholars also lamented the nuisance that social media can warp democracy, enabling the rampancy and uproariousness of populism (Flew & Iosifidis, 2020; Haidt & Rose-Stockwell, 2019), which is shown in the unexpected victory of Donald Trump in the 2016 election and the subsequent democratic crises.

Admittedly, despite the rise of the bottom-up, network-making impact of social media, the existing power structures, and especially the traditional media system, have also been endeavoring to exert their discursive powers to constrain and influence the former, striving to win the power of agenda-setting and construction and empowerment of the meaning of social events, or, in Castells' (2009) words, the "reproduction of the society and the production of social change" (p. 4).

However, no matter what the outcome of the discursive power competition looks like at a practical level, the increasingly tight entanglement of emerging communication technologies and human lives have undoubtedly rendered traditional communication theories incompetent in either capturing or explaining the ever-changing relationship between the *media* and the *audience*. For instance, prior to the advent of the Internet and social media, broadcasting and print media played a preeminent role in grasping audience attention, gatekeeping of information, and exerting significant media effects on audience perceptions (e.g., Goffman, 1974; McCombs & Shaw, 1972). In the digital age, however, rather than passively consuming the news information the elite media provide, the digital citizens' spontaneous and autonomous experience-sharing, topic constructions, and meaning-making have increasingly become the topics of interpersonal discussions (Hampton, Shin & Lu, 2017; Shah, Cho, Eveland Jr., & Kwak, 2005), and even the source and materials of elite media (Harder, Sevenans & Van Aelst, 2017; Meraz, 2009).

Furthermore, although a large number of scholars have realized this profound empowerment of social media on the bottom-up impact, the extant findings are sporadic rather than conclusive—too many mixed and antithetical evidence have been generated, leading to the difficulties and even obstacles to revisiting the traditional theories. To be specific, although everyone appears to have an intuitive feeling about the discursive impact of social media on the elites, we still do not yet have neither a crystal clear nor a coherent account as to, for instance, whether the impact of social media on legacy media and other social actors is issue-sensitive? In other words, whether social media can be powerful in building and setting agendas for some certain issues while shrinking in power when it comes to other issues? If so, what kind of issues do social media have stronger power to set agenda for? Moreover, within the agenda of a given issue, what aspects and dimensions, say, substantive or affective aspects, do social media have stronger power to set agenda for and to influence legacy media?

These queries can further be projected onto a larger social coordinate and background; we can further ask: how do the mass discourses on social media and the traditional media system work to exert their network-making influence? Specifically, how do social media users and traditional media practitioners construct meanings for social issues through interconnecting various elements of a given issue in their discourses and depictions at both substantive and affective levels? How do both networked agendas interplay with each other? Who is more powerful in the agenda-setting and meaning-making process, and at which level of depictions? These queries are central to our understanding of the power play between legacy media outlets and the rising social media, as well as the ever-changing social norms in the current digital society, which is accelerated by the rapid development of the communication technologies.

Against this backdrop, two theories have been combined, not only to revisit and refine the agenda-setting theory, one of the ripest areas of communication research (McCombs & Shaw, 1972), but also to determine the more powerful agenda setter between emerging media and legacy media. The two theories are the intermedia agenda setting (IAS) theory (Boyle, 2001; McCombs & Bell, 1996; Reese & Danielian, 1989) and the Network Agenda Setting (NAS) Model (Guo & McCombs, 2011). As the name suggests, the IAS theory speaks to the agenda-setting effect between various media outlets. For instance, a plethora of studies have examined the agenda flow between elite and non-elite media (e.g., Gustafsson, Svensson & Larsson, 2019; Vonbun, Königslöw & Schoenbach, 2016), traditional and emerging media (e.g., Conway-Silva et al., 2018; Harder et al., 2017), broadcasting and print media (Boyle, 2001), and so forth. The NAS model is also considered the third-level agenda setting, which postulates that the mass media has the ability to interconnect different issues and different elements of a given issue, so as to form a media "gestalt" (Chen, Guo & Su, 2020; Vu, Guo & McCombs, 2014). The NAS model further proposes that the media can transfer their gestalts to the public, so as to tell the audience how to bundle different elements when thinking about an issue (Guo & McCombs, 2011).

As stated earlier, an increasing number of studies has integrated the IAS theory and the NAS model (e.g., Vargo, Guo & Amazeen, 2017), striving to understand which media platform has stronger network-making power (Castells, 2009; 2011; 2013). The integration is manifested in the examination of the agenda flow between traditional and social media at the networked agenda level. To be specific, scholars have grounded their studies in the framework of IAS, treating legacy media and social media as two platform and exploring how the agenda interact across both platforms. Further, the agendas of both platforms they examined are network agenda setting models (Guo & Vargo, 2015; Vargo et al., 2017; Vargo & Guo, 2017).

The combination of the IAS theory and the NAS model has the following merits. First, it provides a way for communication scholars to determine the power relations between the legacy media and the rising social media, which are both striving to win the discursive power of meaning-making and the "reproduction of the society and the production of social change" for contemporary issues (Castells, 2009, p. 4). In other words, rather than exploring the role of social media in a qualitative or intuitive way, the combination of both theories helps provide people with abundant empirical evidence for understanding the power of social media and the relationship between social media and legacy media at a quantitative level. Moreover, the combination of the two theories heeds Castells' (2013) call for inspecting the "network-making power" of media. Specifically, traditional media effects theories mainly describe how the media affects people's perception of an event, an issue, or an individual. However, as Castells (2013) has suggested, the "network-making power" is "the paramount form of power" (p. 47), in that we are in a network-like society, where not only various social actors but also different aspects and dimensions of issues are intertwined and connected (Castells, 2009; 2011; 2013). Therefore, only if the media can bundle various issues or different aspects of an issues, and further transfer such bundled agenda to the public, can the media be considered powerful in terms of network-making. For instance, in the contemporary society, the power of a media lies not only in telling its audience which candidate should be paid more attention to or which attribute of a given candidate should be cared about, but also in combining different candidates and different attributes with different strengths, and transferring this combined, networked agenda to its audiences.

The examination of the combined IAS theory and the NAS model has been carried out to various contexts, ranging from presidential elections (e.g., Vargo, Guo, McCombs & Shaw, 2014) to wars (e.g., Guo et al., 2015). In this dissertation, I strive to develop an account as to how Twitter, the most examined social media platform, interact with the legacy media system in the context of the Black Lives Matter movement in the United States in 2020. The case study of a social movement deems particularly appropriate and important because, as scholars have stressed, the significant role of emerging media is especially reflected in bringing changes to social movements, including revamping the power structure among various social actors involved in the movements, improving mobilization of the movement, facilitating coalition building among activists, and enabling meaning-making (Mundt, Ross, & Burnett, 2018). These features were referred to as the *scaling-up* functionality of social media (Mundt et al., 2018). With this in mind, I shall hereby introduce and elaborate on the case study of this dissertation, the America's BLM movement in 2020.

The Black Lives Matter movement ("BLM Movement" hereafter) is an international social movement initiated by the African American community. As the name suggests, its main purpose was to protest against the systemic discriminations against black people. The campaign officially started after the acquittal of George Zimmerman in the shooting death of African

American teen Trayvon Martin in 2012. Subsequently, a hashtag #BlackLivesMatter became trending on Twitter (Ince, Rojas, & Davis, 2017; Mundt et al., 2018). The BLM movement had re-emerged in 2020 when George Floyd, an African American citizen, died in Minneapolis due to police brutality on May 25, 2020. Because of the alleged utilization of counterfeit bill, a policeman arrested Floyd and knelt on his neck for nearly eight minutes, while Floyd had been begging and saying “I can’t breathe” before death. Since the videos made by witnesses and security cameras went viral, a large number of Americans took to the streets to express their sympathy for the black community and their resistance to the police’s violence and racism, launching protracted demonstrations. The term “I can’t breathe” was also turned into a protest slogan. Multiple American cities were gripped by the months-long protests. Amid the demonstrations and the escalation of the violence among protesters, the Minneapolis City Council announced to restructure the police department and improve transparency. Nonetheless, the demonstrations persisted and oftentimes resulted in escalations of violence.

The movement has once again raised concerns about the human rights among minorities, setting off another climax of the years-long BLM campaign. In addition to a large number of mainstream media tracking and reporting on the movement, social media, such as Twitter, also echoed offline movement and played an irreplaceably important role in mobilization and coalition building (Mundt et al., 2018). Since the emergence and the subsequent popularity of social media, copious studies have largely lent credence to its role in scaling up the offline movements (Keib, Himelboim, & Han, 2018; Mundt et al., 2018; Ransby, 2018). However, how the discussions on social media interact with the agenda on the mainstream media during social movements did not receive same amount of scholarly attention. In other words, insufficient evidence is available to confirm whether the discussions of social media users were affected by the patterns along which the mainstream media's agenda is set, and vice versa. Scholars suggested that with the exponential growth of interactive platforms comes the need to "re-evaluate the agenda-setting power of the news media" (Conway, Kenski, & Wang, 2015, p. 374). Hence, central to my query is, as the most powerful agenda setter at a time, can the agenda of news media still influence the public's agenda effectively? Or is the public agenda on social media strong enough to be immune to the impact of the media agenda, and even in turn affect the media?

Overall, this dissertation is driven by the following three directions. (1) This dissertation builds on the Network Agenda-Setting (NAS) model, investigating how the U.S. mainstream newspapers and Twitter depict the 2020 BLM movement, respectively. To be specific, I strive to delineate the ways in which the media and Twitter discussions interconnect different attributes of the issue at hand, comparing their similarities and differences. (2) Drawing upon the Intermedia Agenda-Setting (IAS) theory, this dissertation further explores how the networked depictions of both platforms interact with each other over time. In other words, I strive to understand which media platform – newspapers or Twitter – is more powerful in setting agenda for its counterpart, and at which attribute agenda level. (3) Furthermore, upon drawing an overall conclusion based on the data analysis, I strive to further understand Twitter's impact on journalists' work routines, published works, as well as today's journalistic norms, through interviewing with frontline journalists qualitatively. In doing so, this dissertation can provide detailed personal insights into the quantitative data analysis, explicating the underlying mechanisms and reasons.

I apply a mixed-methodological approach to achieve these goals. First, I apply computational methods, including network analysis to detecting the NAS models of newspapers and Twitter (Guo, 2012) and time-series analysis to formally inspecting the IAS effects between newspapers and Twitter across time, drawing causal inferences between the two platforms (Meraz, 2011). Next, I conduct in-depth interviews with journalists who serve in the chosen newspapers, asking about their insights into the impact of Twitter on their journalistic works and the professional norms. The journalists' personal experiences and insights will be used to make sense of the findings generated by the quantitative analyses.

In doing so, this dissertation has three potential contributions. First, limited research has hitherto combined substantive and affective attributes of a given issue. This dissertation attempts to enrich the literature by examining both substantive and affective attributes of the issue at hand (i.e., the BLM movement). McCombs et al. (2014) have highlighted that, although earlier NAS researchers can benefit from exploring element associations by the media, the examinations of "the level of redundancy necessary to create these effects among the publics" (p. 793) also deems imperative and awaits more scholarly attempts. This dissertation heeds the call as to examine the redundancy through analyzing the NAS model at the attribute level. (2) According to a recent systematic literature review (Su & Xiao, 2021), decades of IAS studies have generated mixed results regarding the flow of IAS effects between traditional and emerging media. Against this backdrop, the present dissertation strives to provide timely evidence to identify the potentially stronger agenda setter in the case of the BLM movement. (3) Last but not least, given the novelty of the NAS model (Guo & McCombs, 2011), the extant body of knowledge regarding its generalizability, applicability and external validity remains limited. In addition, a majority of the previous NAS research has been confined to a quantitative, descriptive level. However, rather than saying that traditional social media are the main actors of agenda setting, it is better to say that frontline practitioners of traditional media and users of social media are the real agenda setters. While the existing literature does not provide sufficient evidence as to their understanding of and insights into the network intermedia agenda setting between both types of outlets. This dissertation integrates NAS analysis with in-depth interviews with frontline newspaper practitioners. In doing so, it not only examines *how* the networked agendas were set and *how* these agendas flowed between both types of media, but also provides evidence as to *why* the agendas were set in the given ways and *why* the intermedia agenda setting effect shows such a result as exhibited by the quantitative data analysis.

The remainder of this dissertation is organized as follows. In Chapter 2, I review the literature of agenda-setting theory at large, the network agenda setting (NAS) model, the intermedia agenda-setting (IAS) theory, the research perspective of network intermedia agenda-setting, social movement in the era of social media, and Twitter's impact on journalism. These reviews of literature lay a foundation for this dissertation and the formulated research questions, which are elaborated at the end of Chapter 2. In Chapter 3, I explicate the methodologies utilized to address the research questions. Specifically, I show the detailed processes of the content analysis with the help of unsupervised and supervised machine-learning approaches, network analysis, time-series analysis, and the guidelines and procedures of the qualitative in-depth interviews. In Chapter 4. I exhibit the results of these analyses, including the visualizations of the network agenda-setting models of the two examined platforms, the descriptive statistics of the network agenda-setting models, the Granger-causality test results of the intermedia agenda-setting effect between both platforms in terms of substantive, affective, and combined substantive and affective attributes agendas, respectively, as well as the results of the in-depth interviews with journalists. In Chapter 5, I come to general conclusions based on the findings, summarize the implications, takeaways, contributions in theoretical, methodological and practical terms, acknowledge the limitations, and discuss about the research directions for future scholars to further explore and extend, including (1) the nuanced interplay between the agenda of the media and that of the public, (2) the nuanced interplay between the agenda of the traditional media and that of social media, (3) the complexity of Twitter's role in shaping today's journalism, and (4) the methodological advancement in network intermedia agenda-setting research.

CHAPTER TWO

LITERATURE REVIEW

Research Background

The phrase "Black Lives Matter" was first coined on Facebook in 2013 amid the acquittal of George Zimmerman in a shooting death of a 17-year-old Trayvon Martin (Kilgo, Mourao, & Sylvie, 2019). In the subsequent years, the BLM campaign climaxed for multiple times both online and offline and attracted wide scholarly attentions with respect to the role of traditional and social media (i.e., Keib et al., 2018; Kilgo et al., 2019; Zhang et al., 2019). In May 2020, the death of George Floyd, due to the violent police enforcement, has triggered a new round of the BLM movement. Sympathy for the African American community and protests against police brutality have flooded in social media platforms, such as Twitter. In addition, unlike previous BLM campaigns, many also have expressed their strong disaffection of Trump administration along with their concerns about minority rights, as the Trump administration has been considered continuously intensifying the racism since taking office (Gantt Shafer, 2017; McManus et al., 2019).

Akin to the discussions on social media, elite news media have also paid great attention to the BLM movement in 2020. However, the reporting paradigms varied across platforms. Many elite media have devoted efforts to depictions of the unarmed black victims of lethal policing and racial injustice (Lu, 2020), and have reduced the extent of differences between white and black accused criminals in their coverage during the plateau of the BLM movement

(Strine, 2020). However, some media were also found to have excessively focused on the negative ramifications of the protests "primarily by including the voices of claims makers who believe that the movement was responsible for waging a 'war on police'" (Umamaheswar, 2020, p. 7). Against this backdrop, this dissertation seeks to reveal the ways the elite news media and Twitter discussions set agendas for the BLM movement, as well as the agenda interaction paradigm between both platforms.

The Development of the Agenda-Setting Theory

The agenda-setting hypothesis was first coined and termed in the seminal Chapel Hill study (McCombs & Shaw, 1972). However, according to McCombs (2017), before agenda-setting became a theory, two conceptual origins can be traced. First, in the book *Public Opinion*, Lippmann (1922) first proposed the idea that mass media coverage can shape "the pictures" in people's minds. Moreover, the similar idea that news media can play a significant role in shaping the public's perceptions and attitudes also derives from Cohen (1963) who posited that mass media might not tell the public '*what to think*,' but they were very effective in telling the public '*what to think about*' (p. 13). The advancement of Cohen's (1963) proposal witnessed an introduction of a distinction between *cognitions* and *opinions*, namely, a dichotomy of what people think about and what people think. As McCombs (2017) have argued, this dichotomy has been an intellectual breakthrough because it reminded the media researchers that mass media can have strong cognitive impact without necessarily having strong direct impact on opinions and behaviors.

Although both Lippmann (1922) and Cohen's (1963) proposals were more conceptual assumptions without empirical evidence (Cheng, 2016), they served as a breeding ground on which the agenda-setting theory has subsequently been formulated (McCombs & Shaw, 1972). Based upon the 1968 Presidential Election in the State of North Carolina, McCombs and Shaw (1972) conducted a survey analysis and a content analysis to explore the election coverage of the local media in Chapel Hill and people's perceptions about important issues revolving the election. Based on their examination, significant correlation coefficients emerged (McCombs & Shaw, 1972). Specifically, in selecting and exhibiting news, editors, journalists and broadcasters play an irreplaceably vital role in shaping and filtering the reality. Audiences of the media learn not only about a given issue, but also "how much importance to attach to that issue from the amount of information in a news story and its position." (McCombs & Shaw, 1972, p. 176) In a nutshell, the Chapel Hill study has theorized that media are effective in transferring issue saliences to their audiences (McCombs, 2004; McCombs & Shaw, 1972; McCombs & Shaw, 2004).

Over a decade later, Atwater, Salwen and Anderson (1985) probed the mechanism underlying the journalistic practice of agenda setting. Through surveying the newspaper journalists, they confirmed that a majority of the journalists equated objectivity with journalistic ethics and admitted that most newsroom staffs had not being pursuing such reportorial expectations but setting agendas based on interests and norms of news values, particularly in the process of material selection and storytelling (Atwater, et al., 1985).

Time and again, a majority of researchers has confirmed the agenda-setting effect of media at the issue level in various contexts, and also contributed nuanced evidence and findings to the development of the theory at large. Moreover, although the original hypothesis of agenda-setting was derived from the context of politics, in the past few decades, it has transcended such context and been examined in various other contexts, such as international politics (e.g., Livingston, 1992; Peters, 1994; Princen, 2007), environmental issues (e.g., Ader, 1995; Brown & Deegan, 1998; Pralle, 2009), war (e.g., Mazarr, 2007; Rill & Davis, 2008), health (e.g., Ogata Jones, Denham, & Springston, 2006; Reich, 1995; Yano et al., 2002), and human rights and welfares (e.g., Dunaway, Branton, & Abrajano, 2010; Gallager, 2001; Gross & Aday, 2003).

From Issue Agenda-Setting Toward Attribute Agenda-Setting

In the words of the agenda-setting metaphor, this is a causal inference that what is prominent in the media agenda can influence what is prominent in the publics' minds (McCombs et al., 1997). In other words, the original agenda-setting hypothesis speaks to the transfer of salience of the elements in the media's depictions of the reality to the elements in the pictures in people's heads (McCombs & Shaw, 1972). Although theoretically, these agendas include any kinds of elements, and the theory was supported by hundreds of subsequent empirical studies, these studies did not endeavor to differentiate the specific elements in the agenda, leading to imprecision of the theory and the effect it hypothesizes (McCombs et al., 1997). In light of this concern, agenda-setting scholars have proposed the concept of *attribute agenda-setting*, seeking to optimize the original hypothesis and scrutinize the effect at a more nuanced level (McCombs et al., 1997). According to McCombs et al. (1997), the "issue" highlighted in the original agenda-setting hypothesis refers to a single object or a set of objects, whereas the "attribute" in their advanced hypothesis represents the "characteristics and properties that fill out the picture of each object" (p. 704). Moreover, both objects and their characteristics can vary in terms of saliences. For instance, the media can frequently mention the Obamacare as an object, it can simultaneously either endorse or criticize the program. In short, the hypothesis derived from the seminal Chapel Hill study (McCombs & Shaw, 1972) was termed as the first-level agenda-setting or issue agenda-setting, while the hypothesis that the media can also transfer attribute saliency to the publics was termed the second-level agenda-setting or attribute agenda-setting (McCombs et al., 1997).

Upon the proposal of the second-level agenda-setting hypothesis, lively discussions and explications have been initiated among communication scholars. Ghanem (1997, p. 5) and Kiousis et al. (1999) suggested that unlike the first-level agenda-setting, research in the second level has shifted to the set of perspectives or frames that "journalists and the public employ to think about each object." Estrada (1997) also explained that "these perspectives…draw attention to certain attributes and away from others" (p. 246). As a result, McCombs and Shaw (1993) proposed that "media may not only tell us what to think about, but also how to think about it, and consequently, what to think" (p. 65). This argument witnessed a milestone in the development of the agenda-setting theory.

Upon inception, multiple empirical studies have been conducted to confirm the validity of the second-level agenda-setting hypothesis. Analyzing the media coverage and the public opinion reflected by voting results about the 1996 Spanish General Election, McCombs et al. (2000) observed a high degree of correspondence between the attribute agendas of different mass media and the voters' attribute agenda for each of the analyzed candidates, lending full support to the second-level hypothesis. Moreover, through a comparative analysis of Gallup poll responses and coverage in three local newspapers about the New Hampshire primary, Golan and Wanta (2001) suggested that the positive portrayals of John McCain were significantly correlated to people's voting. Furthermore, Goidel and Langley (1995) content analyzed economic news report of the front page of *The New York Time*, indicating that negative news coverage can influence the public opinion. Similarly, through content analyzing the newspaper coverage and broadcast news about the U.S. economy, Hester and Gibson (2003) indicated that news report in a negative valence played a significant predictive role in shaping consumers' expectations about the future of the economy. This finding lent credence to the argument that the media's emphasis on negative information can have "serious consequences for both expectations of and performance of the economy" (p. 73). Using the case of the 2002 Florida Gubernatorial Election, Kiousis and associates (2006) also confirmed the second-level agenda-setting effect of the media on their audiences.

The second-level agenda-setting theory at large has also been tested and examined in various contexts, such as terrorism (e.g., Craft & Wanta, 2004; Fhamy, Cho, Wanta, & Song, 2006), gender (e.g., Angelini & Billings, 2010; Joachim, 2007), health (e.g., Conway, 2013; Lee

& Len-Ríos, 2014), and sports (e.g., Murley & Roberts, 2005; Seltzer & Dittmore, 2009)

Building upon the original proposal of the second-level agenda-setting hypothesis, McCombs et al. (2000) have further dichotomized the concept of "attribute" into two dimensions, namely, *substantive attribute* and *affective attribute*. Taking agenda-setting of political candidates as an example, the substantive attribute agenda pertains to a candidates' policy, ideology, perceived qualification, and personality, whereas the affective attribute agenda pertains to the tone or the valence (i.e., positive, negative, neutral) applied in the coverage of the candidate (see McCombs et al., 2020).

The proposal of the affective attribute agenda-setting is not without theoretical origins. Coleman and Wu (2010) suggested that the theory of affective intelligence is the origin from which the affective attribute agenda-setting hypothesis was derived. The affective intelligence theory argues that "emotions are critical in getting people to pay attention to politics, and that people use emotions, particularly negative ones, to think deeply about their political views" (Coleman & Wu, 2010, p. 318). The typology of attribute has been adopted by subsequent scholars in examining the second-level agenda-setting effects. For instance, anchored by the substantive and affective attribute agenda setting concepts, Coleman and Wu (2010) confirmed that media's emotional-affective agenda corresponded with the public's emotional impressions of political candidates. Kiousis et al. (1999), however, tested the second-level effect within the substantive dimension, suggesting that candidate personality traits and qualifications were significantly correlated with people's impressions.

It is safe to say that the proposal of the second-level agenda-setting theory marks a significant milestone in the development of the agenda-setting theory, bringing the very original hypothesis into a more nuanced, optimized, and refined level (McCombs et al., 1997). The introduction of the typology of substantive and affective attribute has further enriched the theory, leading to abundant empirical research testifying to its notion and assumption.

The Network Agenda Setting Model

With the emergence and the fast popularization of emerging communication technologies, scholars have expressed concerns about the inadequacy of the conventional correlational analysis based on discrete issues or attributes between the media and the public in capturing "the complexity of the current media environment" (Guo & Vargo, 2015, p. 559). Therefore, pundits and scholars have advanced the agenda-setting theory toward a third level, namely, the interconnections among issues and attributes in the media and the transfer of such interconnected agenda to the publics (i.e., Guo & McCombs, 2011). In a nutshell, the third-level agenda-setting hypothesizes that the ways in which individuals connect different elements revolving around an issue is influenced by the ways in which the media make these connections (Guo & McCombs, 2011; Guo & Vargo, 2015).

The third-level agenda-setting hypothesis is originated from the cognitive network theories (Guo et al., 2019), which explores the "pictures" in people's minds (Guo & McCombs, 2011). The third-level agenda-setting hypothesis highlights that people's mental representations of the reality were usually pictorial, diagrammatical and cartographical, rather than centrifugal or discrete (Kaplan, 1973; McCombs, Shaw & Weaver, 2014). In other words, the third-level agenda-setting assumes that the media and the public usually "map out objects and attributes as network-like pictures according to the interrelationships among these elements" (McCombs et al., 2014, p. 792). In light of the networked structure, the third-level agenda-setting is termed the Network Agenda Setting (NAS) Model (Guo & McCombs, 2011), which examines "the location of individual issue nodes in terms of how close they are to the center of a network" (Vargo et al., 2014, p. 301). Hence, network analyses were typically used to visualize the media "gestalt" constituted by the interconnected objects and attributes (e.g., Chen et al., 2019; Guo et al., 2015; Guo et al., 2019; Vu et al., 2014, p. 672).

Although the advent of the NAS model witnesses another stage of development of the agenda-setting theory in the recent decade (Guo & McCombs, 2011), it is an offspring of a gestalt perspective rooted in the earliest days of agenda setting (Vu et al., 2014). Gestalt refers to a collective mixture of major public issues and news topics portrayed by the mass media, it also describes what the public will "experience and absorb as they are exposed to the media agenda" (Vu et al., 2014, p. 672). This perspective well aligns with Lippman's (1922) proposal of "pictures" in people's minds. It is safe to say that the first- and second-level agenda-setting hypotheses did not really attempt to depict the "pictures," because both were confined to the examinations of discrete elements rather than networked elements; therefore, the alleged pictures revealed by the first two levels of agenda setting are only linear pictures rather than diagrammatical pictures. The NAS model, however, serves as a substantial attempt seeking to delineate the cartographical pictures in people's heads (Lippman, 1922).

The first empirical research testing the NAS model was conducted by Guo and McCombs (2011). Adopting the data originally captured for Kim and McCombs' (2007) examination of the third-level agenda setting, the authors revealed significant connections between each pair of attributes based on the frequency of their co-occurrence in the same news coverage. Specifically, the authors have performed network analyses to examine the media and public agendas of the attributes of the political candidates in Texas gubernatorial and U.S. senatorial elections. They found that the ways in which the media depicted the attributes of the candidates significantly influenced the ways in which "the picture in the public's minds." This study has witnessed the birth of the third-level agenda-setting as a new advancement of the traditional agenda-setting theory. In the meantime, considering the theoretical essence of the third level, it is further termed as the Network Agenda Setting (NAS) model (Guo & McCombs, 2011).

Although the NAS model "is still in its infancy" (Guo, Mays & Wang, 2019, p. 566), abundant studies have devoted themselves to the investigations of the validity of the NAS model. Analyzing five years of aggregated data from 2007 through 2011, Vu et al. (2014) found that the media were able to bundle issues and transfer such saliency to the public's mind. This study not only confirmed the hypothesis of the NAS model but also extended its scope through using an aggregated, longitudinal data. Contextualized in the 2012 Presidential Election, Guo and Vargo (2015) analyzed both the media content and tweets revolving around the presidential candidates. Based on the results, the authors confirmed that Twitter, albeit being a strong agenda setter in the digital age, was still significantly influenced by the traditional media's agenda, not only in terms of single-issue agendas but also entire networks of issues (Guo & Vargo, 2015). The results demonstrated that "the NAS model and its unique focus can potentially enrich the understanding of other communication and social science theories and concepts" (p. 558). Likewise, Kiousis et al. (2015) suggested that the third level for stakeholder network associations exhibited a strong linkage between the media and the public.

Some recent NAS studies have not only testified to the initial hypothesis postulated by the seminal work (i.e., Guo & McCombs, 2011), but also extended the scholarly examinations of the NAS model into an international context. In other words, these recent works have used samples from countries other than the U.S. to test the NAS model, striving to consolidate its external validity (Barratt, Ferris & Lenton, 2015).

For instance, using the context of the Iraq War, Guo et al. (2015) examined how the newspapers in the U.S., China Mainland, Taiwan and Poland depict the issue at the networked level. The study found that an emphasis of bundled message attributes highlighted the larger context of these attributes on the media agenda. Moreover, the focus of the bundles of the message attributes also presented a more nuanced measure of salience "in contrast to the traditional focus on the frequency of discrete objects or attributes to define the media agenda" (p. 343). This study, albeit contributory to the knowledge of the NAS model, only explored how the respective media depicted the issue, without further examining whether and how it influences the network agendas of the public, using either survey of online discussions. That being said, several subsequent studies have followed the research pattern it provided (Guo et al., 2015) while extended its research scope through analyzing the interaction between the media's network agenda and the public's.

To gain a better understanding the nationalistic sentiment amongst Chinese people, Chen et al. (2019) investigated the network agenda flow between different accounts in Weibo, a Twitter-like Chinese social media. They differentiated Weibo accounts into ordinary individual users, Weibo influencers, and official, organizational users, suggesting that, in general, media agenda still have a stronger impact on the formation of the Weibo agenda, while in terms of the construction of the nationalistic discourses, the network agenda setting followed a bottom-up direction, namely, the ordinary users were found to be more influential in setting nationalistic network agendas for the organizational accounts.

Furthermore, Guo et al. (2019) have introduced the NAS model into a multi-national context, namely, the South China Sea dispute. The authors examined how the traditional media in the U.S., China, the Philippines, and Vietnam depicted this territorial dispute in terms of the networked attribute-agenda level, and how these networks of the traditional media in the respective countries interact with discussions in the Twittersphere, which is contributed by the digital citizens worldwide. In terms of the agenda flow between the traditional media and Twitter, their results suggested that the traditional media had an overall stronger power to transfer their networked attribute agendas of the South China Sea dispute toward the Twitter users. In terms of the nuances across the traditional media in the respective countries, the authors indicated that the U.S. media, among all the chosen media, showed more prominent impact on the discussions in Twitter. In doing so, this not only addressed the query as to whether traditional types of media still possess significant impact on the agenda of social media in the digital age and at the networked level, but also provided nuanced insights into national differences (Guo et al., 2019).

To bolster the conclusion drawn by Guo et al. (2019) and to consolidate the external validity of the NAS model, which is “still in its infancy” (Guo et al., 2019, p. 566), a subsequent study replicated the research pattern of Guo et al. (2020) while used the context of the Senkaku Islands dispute (i.e., Su & Hu, 2020). Examining the causal relationships between the network agendas of the U.S., Chinese, and Japanese mainstream newspapers and the discussions revolving around the dispute in Twitter, the authors have come to the nuanced conclusions with Guo et al. (2019), suggesting that Twitter was more powerful in setting the networked agenda for the newspapers instead of the other way around. Moreover, in terms of the cross-national comparisons, the authors have also indicated that the Chinese media have exhibited a stronger influence on Twitter, followed by the U.S. media (Su & Hu, 2020). The findings have provided nuanced evidence against Guo et al. (2019).

Another cross-national NAS research was contextualized in the Hong Kong’s anti-extradition bill movement. Following the research vein (i.e., Guo et al., 2019; Su & Hu, 2020), Su, Hu and Lee (2021) investigated the networked attribute-agenda flow between Twitter discussions and newspapers in Hong Kong, China Mainland, U.S., and U.K. Using the network analysis and time-series analysis, the authors found that Twitter exerted a stronger influence in predicting newspaper coverage. However, when it comes to more nuanced attribute-agenda level, the findings further showed that Twitter's impact on newspapers were mainly confined to the substantive attribute level of agenda, while it showed little to no impact on newspapers in terms of the attribute agendas and the bundled substantive and attribute agendas. These findings not only confirmed Twitter's increasingly significant impact in the digital age, bolstering the prior piece about the Senkaku Islands dispute (i.e., Su & Hu, 2020), but also provided insights into the limitations of its impact. Specifically, the findings denoted that both media platforms, notwithstanding reciprocating at the substantive attribute level, tended to depict the movement independently in terms of the tones and valences with which the stories were told.

According to the findings of these five extant NAS studies in the international context, one can infer that: (1) the basic theoretical framework and methodological pattern for NAS research has been relatively mature and fixed, which is shown in the methodological consistency in these studies (Chen et al., 2019; Guo et al., 2015, Guo et al., 2019; Su et al., 2020; Su & Hu, 2019); (2) The external validity of the NAS Model is still limited, because the results are found to vary with the research contexts. As previous scholars have argued, replications help confirmation of external validity of theories (Ross & Morrison, 1989), scholars can benefit from following along the matured research vein while expanding the size and scope of data to continue to enrich the theory.

Another advancement brought by the NAS research pertains the methodology used to detect the public's agenda. The original agenda-setting research analyzed survey data to represent *what* the public think and *how* they think about an issue (McCombs & Shaw, 1972). However, NAS researchers have started to use social media data to represent the public agenda. For instance, Vargo and associates (2014) constructed the public agenda through analyzing the users' discussions in Twittersphere and found that distinctive audiences melded the agendas in traditional media of various types. Moreover, Guo and Vargo (2015) also built the public agenda through big data analytics on Twitter, revealing that traditional media did not lose its grip in affecting public opinion online. Similarly, Chen et al. (2019) used Weibo to represents the public agenda in China. Scharkow and Vogelgesang (2011) argued that online data allows researchers to perform "unobtrusive observation" and "promises to be a powerful method for the measurement of follow-up communication" (p. 106). Such argument is also well-aligned with Roberts, Wanta and Dzwo's (2002) argument about the close tie between traditional media and online discussions – "[m]edia coverage apparently can provide individuals with information to use in their Internet discussions" (p. 464).

In summary, the NAS model and subsequent research revolving around the model have brought the following advancements to the agenda-setting theory. First, in the theoretical term, the NAS model investigates how media interconnect different elements, including issues (Vargo et al., 2014), substantive attributes of issues (Guo et al., 2015), and affective attributes of issues (Guo et al., 2019), and how they transfer these interconnected elements to the public (Vargo & Guo, 2017; Vargo et al., 2018). These attempts well aligned with Lippman's (1922) explication about how the media can construct pseudo-environments, linking “the world outside and the pictures in our heads.” In the methodological term, the NAS model has the following three contributions. First, the NAS research utilizes social media data to represent the public agendas, which guarantees unobtrusive observations from the researchers. Second, rather than analyzing the correlations across discrete issues and attributes (McCombs & Shaw, 1972), the NAS model visualizes how the media bundle different elements, reflected in the way of bundling through nodes and edges (Guo, 2012). In this way, the data analysis itself can present the network agenda more intuitively and vividly; and a direct comparison of the visualizations of different network agendas can also help researchers observe commonalities and differences of nodes and edge between various platforms. Lastly, the NAS research applies time-series analysis to gauge agenda-setting effect in short time-lags (e.g., one day). For instance, it explores whether the agenda-setting power of a given platform can last. In doing so, the NAS research can provide evidence about the variations and fluctuations of the agenda-setting effects in small time units, indicating more nuanced causal inferences across various platforms. In contrast, conventional agenda-setting research can only infer causations within a relatively large time span. For example, it can only observe how media coverage before an election have affected public opinion during or after the election (e.g., Coleman & Wu, 2021; Hyun & Moon, 2016). However, the NAS model brings the examination into a daily-, or even hourly-, basis (Guo, 2020; Guo & Zhang, 2020).

Intermedia Agenda Setting

Rather than confining to the association between news media and the public (e.g., Coleman, McCombs, Shaw, & Weaver, 2009; Dearing & Rogers, 1996; Kosicki, 1993; McCombs, 2005; McCombs, Overholser & Jamieson, 2005; Mrogers & Wdearing, 1988), agenda-setting researchers have argued that the agenda-setting effect can also take place between media outlets. In other words, the way in which one media outlet set its agenda can affect that of another media. This effect is termed intermedia agenda setting (IAS), denoting the interaction of media agendas across media platforms (Boyle, 2001; Lopez-Escobar, Llamas, McCombs, & Lennon, 1998; Meraz, 2001; Ragas & Kiousis, 2010; Sweetser, Golan & Wanta, 2008).

As a sub-theory of agenda setting, the IAS research has gone through several phases of development due to the revolution of communication technologies. These stages can be roughly divided into two periods – before and after the emergence of social networking sites.

IAS Research Prior to the Emergence of Social Media

Before the emergence of social networking sites, IAS researchers have mainly devoted themselves to the investigations of the interplay between traditional types of media (e.g., Lopez-Escobar et al., 1998; Schooler, Sundar, & Flora, 1996; Reese & Danielian, 1989). For instance, Reese and Danielian (1989) examined the agenda flow between several impactful newspapers in the United States. They found that the issues covered by *The New York Times* were more likely to lead the coverage of other print media, including important outlets such as *The Wall Street Journal*, *the Washington Post*, and *the Los Angeles Times*. Similarly, through content analyzing health articles in two city newspapers and two reference city newspapers, Schooler et al. (1996)

found that one of the city newspapers responded well to the program whereas the other did not show any IAS effects. In this case, the examination of the IAS effects was confined to the interplay across metropolitan newspapers of different scales and levels. In general, IAS research on the same type of media showed that elite media were more likely to set agendas for non-elite media. This conclusion is further bolstered by a systematic literature review on the published IAS research within a 23-year span (Su & Xiao, 2021).

Apart from the investigation between elite and non-elite media, a sizable portion of studies have also devoted to the examinations of traditional media but of different types. To be specific, they inquired into the agenda flows between print media, broadcasting outlets, and other forms of traditional media. Lopez-Escobar, et al. (1998) investigated the IAS effects between newspapers' agenda and televisions' agenda for a Spanish election at the initial two agenda-setting levels. The authors suggested that, at the first agenda-setting level, the Spanish newspapers' agenda affected the television news' agendas. However, at the second agenda-setting level, newspapers' agenda affected both the televisions and newspapers' substantive attribute agendas, while reciprocities were found at the affective attribute agenda-setting level (Lopez-Escobar, et al., 1998). Golan (2006) suggested that in the morning *New York Times* was influential to set agendas for evening news programs in three television channels. Vliegenthart and Walgrave (2008) also found that in Belgium, newspapers had stronger influence on television than the other way around.

In a nutshell, in the era when traditional media dominated the news content production and information dissemination, findings of the IAS studies showed the following two trends: (1) newspapers have stronger agenda-setting impact on other types of media; and (2) elite media have the capability to set agendas for non-elite media.

IAS Research in the Digital Age

The advent of the Internet has rendered these two largely agreed unidirectional intermedia agenda-setting effect incompetent. The diversification of the forms of social media platforms and the drastic differences in the power of social media platforms to influence the agenda-setting of traditional media amid different events and during different time periods have triggered a large and growing body of IAS research. The complex and sophisticated interactions between traditional and social media have generated a new debate as to “who leads whom” (Vargo & Guo, 2017, p. 1047).

With this in mind, a systematic literature review (Su & Xiao, 2021) has overviewed the decades of IAS studies and summarized the following research veins with regard to the directionality of agenda flow in the digital era: (1) from a traditional media to an emerging media, (2) from an emerging media to a traditional media, (3) from one emerging media to another emerging media, and (4) reciprocal effects between emerging media and traditional media (Su & Xiao, 2021).

Agenda flow: from traditional toward emerging media. A majority of studies has confirmed that traditional media, albeit weakening in its impact on the public, still has the ability to set agendas for emerging media. For instance, Groshek and Groshek (2013) examined the IAS effects between traditional media (*The NYT* and CNN) and social media platforms (Facebook and Twitter), suggesting that traditional media had stronger abilities to set agendas for social media platforms in terms of both political and cultural coverage. Harder and associates (2017) investigated the TV reports, newspaper coverage, and Twitter discussions about the 2014 Belgium election campaign, yielding three important findings. First, online media outlets were found to strongly affect other media that publish less often. Second, slow newspapers often precede other media's coverage. Three, within Twitter discussions, tweets of media actors were found to have vastly stronger agenda-setting ability than other actors do (Harder et al., 2017). Analyzing the traditional and social media coverage between 2009 and 2016 of the Dutch policy reforms to raise the retirement age, van den Heijkant and associates (2019) found that traditional news media had stronger agenda-setting impact on social media than the other way around.

Some scholars have argued that, although the rise of social media has generated alternative findings, the *traditional-to-emerging* direction is still more likely (e.g., Ceron, Curini & Iacus, 2016; Kim, Gonzenbach, Vargo, & Kim, 2016; Vargo et al., 2018; Yang & Kent, 2014). Vargo et al. (2018), for instance, indicated that emerging media were responsive to the agendas of fake news, but to a lesser degree compared to legacy media. Yang and Kent (2014) found that mainstream media coverage significantly affected the visibility of social media. Through big data analysis, Ceron et al. (2016) suggested that the online version of traditional media keeps the power of first-level agenda setting even though a significant difference between the slant of traditional news and the Twitter sentiment appeared. Kim et al. (2016) also demonstrated the power of newspapers in predicting agenda of Twitter in a political advertising context.

To sum up, despite the rapid growth of social media and its increasing power of agenda-setting, many scholars are still confident about traditional media's role in shaping the agenda of social media, based on their empirical findings. They argued that social media are more likely to echo the agenda set by traditional media, rather than independently setting agendas and transferring their agendas to the traditional, elite-hold media. This is perhaps due to the fact that there are typically various decisive factors that serve as the antecedents of traditional media's agenda-setting, including their political stances, ideological camps, sponsorships, and sources of funds. Therefore, traditional media's agenda- -setting were not prone to be adjusted or affected simply by discussions in social media.

Agenda flow: from emerging toward traditional media. Unlike the crystallized consensus on traditional media's role in shaping other media's agendas in the earlier age, some scholars have observed the potential existence of a bottom-up effect of social media in influencing their traditional counterpart. For instance, Meraz (2011) investigated the agenda flow between traditional media and blogs, indicating that traditional media were unable to set agendas for political blogs. Comparatively, political blogs, particularly those ideologically diverse ones, were able to set agenda for both the online news and newsroom blog of traditional media. Meraz (2011) argued that traditional media's singular agenda-setting influence has diluted in the digital age. Furthermore, Rogstad (2016) analyzed the Norwegian Twitter and mainstream media agendas and found that Twitter, rather than echoing what is covered by the print media, contributed to “an expansion of the elite” (p. 142). Hence, the author argued that Twitter has become a platform “for eloquent and media-savvy people outside the traditional political, economic, or academic elites” (p. 142). Vargo and Guo (2016) also found that two elite newspapers, *The New York Times* and *The Washington Post*, were no longer controlling the news agenda. Yet, both elite papers were more likely to be influenced by the agenda of online partisan media.

Analyzing the case of an earthquake in Chile, Valenzuela, Puente and Flores (2017) investigated the agenda interaction between journalists on broadcast news and Twitter and suggested a “reciprocal but asymmetrical relationship,” in which TV news “adopt[ed] the issue agenda of journalists’ on Twitter” (p. 631). Vonbun-Feldbauer and Matthes (2017) also indicated that the agenda-building process was a multi-directional process shaped by the channel characteristics stability and flexibility. Contextualized in China, an authoritarian regime where all media outlets are strictly controlled by the authorities, Su and Xiao (2020) found that WeChat public account agenda was able to set the agenda of China’s metropolitan newspapers.

In a nutshell, a growing number of studies have documented the rapidly increasing influence of social media in shaping the agenda of traditional media, rather than vice versa. This denotes that traditional media practitioners have started turning to social media for topics.

Agenda flow: reciprocity between traditional and emerging media. Additionally, many studies have argued that the IAS effect between emerging and traditional types of media are more likely to be reciprocal rather than unidirectional, notwithstanding asymmetrical. In other words, both types of media can influence the agenda of their counterparts, while the nuances hinge more upon factors such as event, timing, context, and others.

In 1998, Lopez-Escorbar et al. (1998) found that intermedia agenda setting effects are not always unidirectional. Instead, they can be multidirectional when it comes to different levels of agendas and different types of media outlets. This argument is echoed and bolstered by a subsequent research on the IAS effect across television, advertisements and blogs during the 2004 U.S. Presidential Election (Sweetser et al., 2008). Specifically, Sweetser et al. (2008) examined the agendas of the candidate-controlled public relations tools, candidates' blogs, and major TV news networks, finding that blogs and political ads were more likely to set the agenda for TV. In the authors' words, their study provided "evidence of a reciprocal intermedia agenda setting effect…[and] reinforce the Lopez- Escobar et al. (1998) results, which suggested intermedia agenda setting is not always unidirectional but may be multidirectional" (p. 212-213).

Moreover, through assessing issue emphasis in Twittersphere and newspaper coverage of the 2016 U.S. presidential election, Conway-Silva and associates (2018) pointed to a reciprocal relationship, where newspaper had an overall greater impact while Twitter also exhibited "the potential to break free from and influence traditional media gatekeeping" (p. 469). Scholars (e.g., Newman, Dutton & Blank, 2012) highlighted that social media have become the 'Fifth Estate' that developed a synergy with their traditional counterparts, sometimes contributing to "an expansion of the elite" (Rogstad, 2016, p. 142). Likewise, Su and Borah (2019) analyzed the newspaper coverage and Twitter posts about climate change, examining the agenda interplay between both platforms. The authors also indicated a reciprocal rather than unidirectional influence between newspapers and Twitter. Moreover, they highlighted that timing is an important factor upon which the flow of IAS effect is contingent. Specifically, Twitter was found to have stronger IAS effect on newspapers in terms of breaking news, while newspapers were more likely to set agendas for Twitter in terms of on-going debates, which are of lower timeliness.

Reciprocal effects between traditional and social media have also been examined and observed in multiple contexts. For instance, Luo (2014) investigated the agenda flow across three types of media in China: online discussion forums, metropolitan newspapers, and party newspaper. The author found revealed bidirectional agenda-setting effects between online forums and traditional media, suggesting that "online public opinion has become a competing agenda-setting force in contemporary China" (p. 1289). Furthermore, Guo (2019) explored the IAS effects between online news websites and official media in China, also showing reciprocal effects between both platforms.

The mechanism of this reciprocity is based on the following three antecedents. First, social media can transform the societal structures by creating an uncoerced public sphere, which nurtures the growth of deliberation through the unmediated diffusion of news (Meraz & Papacharissi, 2013). Second, social media can reduce the transaction costs of content creation and dissemination, providing a relatively egalitarian access for ordinary audience (Benkler, 2006). Lastly, traditional media, as controlled by political and economic elites, still possess considerable agenda-setting impact on the public (Vargo et al., 2018). Integrating the still strong impact of traditional media and the growing influence of social media, reciprocities were more likely than unidirectional effect, regardless of the directionality with which the agenda flows (Conway-Silva et al., 2018; Guo, 2019; Luo, 2014; Newman et al., 2012; Rogstad, 2016; Su & Borah, 2019). A systematic literature review of the IAS research published between 1997 and 2019 also confirmed that, a majority of IAS research comparing the IAS impact between traditional and social media, found reciprocal rather than unidirectional effects (Su & Xiao, 2021).

The Network IAS Perspective: An Integration of the NAS Model and IAS Effect

The initial NAS model has been extended to examine the "networked intermedia agenda setting" (Vargo et al., 2018, p. 2030; Vargo & Guo, 2017). According to Vargo et al. (2018), this approach integrates the NAS model and IAS research to investigate the transfer of networked agendas "from media to media" (p. 2030). In other words, the network IAS dictates that the way one media platform bundles various elements could influence the way another media bundles these elements (Vargo et al., 2014; Vargo et al., 2018; Vargo & Guo, 2017).

Although network intermedia agenda setting is a relatively new research direction, a number of empirical studies have been conducted and lent support to the flow of networked IAS effects across various types of media. For instance, contextualized in the 2012 U.S. presidential election, Guo and Vargo (2015) examined the transfer of networked information between top American newspapers and Twitter. The authors suggested that traditional media influenced the public opinion in Twittersphere (Guo & Vargo, 2015). Moreover, Vargo and Guo (2017) suggested the homogeneity and reciprocity across media agendas. They found that the networked agendas of elite newspapers were led by that of online partisan media, suggesting that "intermedia agenda–setting effects varied by media type, issue type, and time periods" (Vargo & Guo, 2017, p. 1031). Though bottom-up effect of online media on traditional media emerged in specific cases (e.g., Vargo & Guo, 2017), most of the empirical evidence have confirmed the stronger impact of traditional types of media on social media such as Twitter. Furthermore, Vargo et al. (2018) found that partisan media were more likely susceptible to the fake news agenda while emerging media responded to the fake news agendas at a lesser degree. Guo et al. (2019), through analyzing the IAS effects between three countries' newspaper agendas and Twitter's agenda for the South China Sea dispute at the network agenda setting level, indicated that the way traditional media bundled issues and attributes about this geopolitical conflict was more likely to shape the way people bundle the same elements when discussing about the issue in the Twittersphere.

A handful of studies have also suggested Twitter's role in shaping traditional media in terms of the bundled elements (i.e., the NAS model). A replication of Guo et al. (2019) showed that amid the Senkaku Islands dispute, there are reciprocal while asymmetrical IAS relationships between Twitter and newspapers in various countries, but of nuanced levels. Specifically, the authors found that discussions in Twitter affected the agenda of newspapers, while the reciprocities emerged more frequently between Twitter and U.S. newspapers (Su & Hu, 2020).

Moreover, Su et al. (2020) also bolstered the argument as to the reciprocal while asymmetrical relationship between Twitter and newspapers in terms of the agenda-setting of Hong Kong's political movement. The authors indicated that the IAS influence between Twitter and newspapers were reciprocal, but Twitter exhibited a relatively stronger role to predict the agenda of newspapers about the movement. More importantly, the study showed that Twitter's impact was stronger in terms of substantive attribute agendas; yet it's impact on newspapers significantly shrinks in terms of affective attribute agendas.

In sum, studies in the past decade have endeavored to combine the network agenda setting model and the intermedia agenda-setting theory, striving to obtain a better understanding as to the detailed mechanism underlying the transfer of NAS models between various media platforms. The extant knowledge generated by these studies showed that the impact of an individual media outlet in terms of transferring its networked agenda to another media outlet can be determined and varied by the following factors: (1) the level of agenda (e.g., issue agenda, substantive attribute agenda, affective attribute agenda, etc.), (2) the media and platform examined, and (3) the context in which the research is performed. In light of the novelty of the theories (Guo et al., 2019) as well as limited body of existing research dedicating to the combination of both perspectives (Vargo et al., 2018), it is safe to say that a tentative conclusion as to which type of media is more powerful in transferring its networked agenda toward its counterpart still is hard to be inferred.

Social Movement in the Era of Social Media

In each historical era, distinctive forms of communication and organization have shaped and characterized social movements. Prior to the emergence of the Internet, communication tools used in social movements were largely limited, resulting in fairly low efficiency of social movements in terms of mobilization and escalation. For instance, liberty poles and pamphlets were used by American people in their revolutionary agitation against Great Britain in the 18^{th} century. Print publications, such as newspapers and books, were used by abolitionists as well as African Americans during the Civil Rights movement (Kreimer, 2001). Scholars have argued that social movements that were mobilized and facilitated by these traditional communication tools had the following features (e.g., Hintzen, 1989; Tarrow, 1995; Youmans & York, 2012). First, historical social movements were typically initiated and practiced in an elite-to-mass direction (Tarrow, 1995). To be specific, the elites, including political officials, business tycoons and celebrities, enjoyed the privileges to access information, right to speak, and ability to mobilize movements, whereas the mass could barely exert bottom-up impact (Hintzen, 1989). Second, the social movements were of low efficiency due to the inconvenience of information flow through print and broadcast media (Youmans & York, 2012).

The emerging communication technologies have drastically revamped not only the landscape of media environment itself but also the ways in which social movements were initiated, practiced and proceeded. Scholars have pointed to three ways through which social movements were influenced by emerging media shall be detailed.

First, emerging media, particularly social networking sites (SNSs) such as Twitter, Facebook and Instagram, have become important resources for the mobilization of collective actions and "the subsequent creation, organization, and implementation of social movements around the world" (Eltantawy & Wiest, 2011, p. 1207). Given the considerable level of penetration of social media in today's digital society, technology-savvy activists can take full advantage of social media to initiate and organize a broad spectrum of activities such as public protests and demonstrations (Eltantawy & Wiest, 2011). For instance, during the anti-war movement in Iraq in the year of 2003, the Internet was extensively utilized by the social movement leaderships to create consciousness among decentralized networks, which finally mobilized and engaged more than ten million people to demonstrate (Cortright, 2007). As scholars have stressed, successful mobilizations of social movements largely hinge upon the extent to which a group has shared interests, common self-identity, and awareness and assessment of the level of governmental repression (e.g., Harlow, 2012; Tilly, 1978). Networked information dissemination pattern enabled by social media can facilitate such mobilization (Lopes, 2014; Rolfe, 2005). More specifically, it helps raise people's awareness of governmental pressures, thereby concentrating people's attention to how government poses threat to their own interests, strengthening their motivations of participation (Rolfe, 2005; Theocharis, Lowe, Van Deth, & García-Albacete, 2015).

Second, in addition to mobilization, social media can also play a critical role in facilitating and escalating social movements. Scholars have termed these social-media facilitated movements as "web-fueled social movements" (Eltantawy & Wiest, 2011, p. 1207) or “cyberactivism” (Sandoval-Almazan & Gil-Garcia, 2014, p. 365). This facilitative role of social media in shaping social movements is due to two mechanisms: its networked information dissemination pattern (Olanrewaju, 2020), and its egalitarian access (Daubs, 2017).

For instance, in the 2019’s Hong Kong protest against the Extradition Bill, Hong Kong Internet users have circulated online information such as videos and photos to document the government’s frail responses and police brutality against the protestors (Shao, 2019). However, initially, it was the activity leadership who shared out the information; then, the Internet users following these leaderships spread out to their followers, thus formed a networked dissemination pattern (González-Bailón & Wang, 2016; Stieglitz, S., & Dang-Xuan, 2016; Stockmann & Luo, 2017). Hence, the spreading scale have been indexed exponentially. As such, online information has played a pivotal role in *escalating* and *exacerbating* the social movement among the civilians (Qiang, 2011).

Third, in addition to mobilization and escalation of social movements, SNSs are also beneficial in nurturing a deliberative democracy at a societal level (Halpern & Gibbs, 2013; Loader & Mercea, 2011). Habermas (1989) conceptualized deliberation as an interchange of rational and critical arguments among a group of people, elicited by a commonly shared issue, whose main concern is to come up with a solution acceptable to every individual in the given group. Subsequent scholars have also conceptualized deliberative democracy as an idealized category within the broader notion of discursive participation (Delli Carpini, Cook, & Jacobs, 2004; Halpern & Gibbs, 2013). Based on this concept, social media can enable decentralized communication of many-to-many as each individual user was provided egalitarian access and was equally entitled to express their opinions and have dialogues with each other in a free marketplace of opinions (Halpern & Gibbs, 2013; Janssen & Kies, 2005). Further, citizens of such deliberative democracy will be able to challenge the monopoly control of media production and dissemination by state and commercial institutions (Loader & Mercea, 2011).

Last but not least, despite these three merited impacts of social media, there are also potentially negative impact of social media on democratic movements. One of the traps that merit in-depth discussion is that the decentralized information dissemination landscape may lead to the lack of efficient organization, and further lead to irrationality and populism (Engesser, Ernst, Esser, & Büchel, 2017; Gerbaudo, 2018; Groshek & Koc-Michalska, 2017). The ability to express opinions and personalize one's own space can trigger the "filter bubble," which refers to the behavior that one surrounds him or herself only with information that is in line with their pre-existing ideologies and reduce their exposure to the information at odds with their values. Consequently, such selective exposure could lead to the development of false evidence, upon which one may make flawed judgments and decisions during social movements, activities and political campaigns (Bartlett, 2014). This might be a potential dark side of social media's impact.

In light of these implications of social media in the context of social movements, communication scholars should be concerned with the following things. First, with the advent of emerging media, there has been a transition of research question in the field of social movement studies, that is, from focusing on multiple actors (i.e., political figures, grassroots, etc.) in social movements toward focusing on the role that emerging communication technology plays in shaping social movements. Put differently, in the past, there was an evident power disparity among different actors, such as political leaderships, celebrities, and ordinary people, in terms of influencing the progress and trajectories of social movements in which they were involved. However, such power disparity might have been reduced or eliminated by emerging communication technology and its unique functionalities. Therefore, scholars should revisit and rethink the powers of different actors in social movements in the current digital age.

Second, the academia has witnessed not only the aforementioned shift of research focus but also less academic consensus. For instance, in earlier times, elite national media were documented to be the most and the only powerful outlet to set media agendas, whereas the emergence of social media have challenged and deconstructed such monopolized agenda-setting power of traditional media, leading to a multi-polar landscape of agenda-setting (Conway et al., 2015). Therefore, scholars examining the intermedia agenda-setting effects suggested that in the current digitalized society, social media, such as Twitter, has been creating a synergy with traditional media, and the agenda flow between traditional and social media are more likely to be reciprocal and bi-directional, instead of non-complementary or unidirectional (Newman, Button, & Blank, 2012). As such, social media can create an "e-democracy" that enables a profound revolution in social movements (Meraz & Papacharissi, 2013).

In short, the emerging media landscape not only has multiple merits facilitating social the participatory culture and the deliberative democracy, but also brought in potential traps. Scholars should be concerned with new challenges and queries such as how the power structure of traditional actors were changed and how these new technologies influenced the conventional journalistic practices, including agenda-setting. This dissertation, through contextualizing in the BLM movement and examining how Twitter interact with traditional media in terms of network agenda setting, heeds the call to uncover and understand the "indexing role" of Twitter in the current digital age (Valenzuela et al., 2017, p. 631).

Twitter's Impact on Journalism

With the glaring penetration of social media, its impact is not only confined to social movement but also to all walks of life. Some scholars argued that social media is a *hypermedia* because, unlike other forms of media, its operation does not require any institutional support (e.g., Barrett, 1994; Howard, 2002). The information on social media permeates individuals' daily lives, shaping perceptions and behaviors, but also has an impact on professional work in all walks of life. Akin to teachers' using social media as an effective tool in the class activities they designed, journalists may also turn to social media, such as Twitter, as a useful tool to assist their journalistic works. Indeed, journalists use Twitter widely (Lee, 2015; McGregor & Molyneux, 2020; Molyneux, 2015; Vis, 2013). The comprehensive use of Twitter among journalists is, on the one hand, spontaneous; on the other hand, it can be a result of encourage or requirement by the organizations where the journalists work (Lee, 2015; McGregor & Molyneux, 2020). When emerging communication technologies, and social media in particular, started rising to prominence, a series of research has investigated the ways in which the new expectations and norms of emerging media shifted journalistic routines, including the determination as to the salience placed on an issue and gatekeeping function (e.g., Groshek & Tandoc, 2016; Hermida, 2013; Johnson, Paulussen & Van Aelst, 2018; Kogen, 2012; Lasorsa, Lewis & Holton, 2012; Lee, 2015; McGregor, 2019; Parmelee, 2013; Powers & Vera-Zambrano, 2018; Prasad, 2019).

Parmelee (2013) interviewed political journalists at U.S. newspapers during the 2012 presidential campaign. The author summarized three advantages of Twitter in assisting journalistic works of political reporters. First, Twitter is helpful in “finding and tracking breaking news.” Second, Twitter is ideal for “crowdsourcing.” Third, Twitter can help maintain “awareness remotely of the activities and thoughts of individuals deemed important for news stories” (Parmelee, 2013, p. 297). Meanwhile, Twitter was also found to have negative impact on journalism, including time-wasting, distractive, and being able to “lead to an echo chamber effect that distorts the importance of certain topics” (Parmelee, 2013, p. 297).

Through interviewing 11 journalists from several U.S. national and local newspapers, Lee (2015) inquired about the ways in which these journalists used, and were affected by, Twitter. Lee (2015) revealed that the utilization of Twitter among journalists are largely motivated by organizational expectations. Namely, the organizations the journalists work for have encouraged them to use social media such as Twitter and Facebook to aide “reporting and to connect with audiences” (p. 226). However, the consequences of using Twitter have both pros and cons. For instance, Lee (2015) reported that the journalists had a positive attitude toward Twitter in terms of speed-driven news practices, insular conversations across journalists, and approaching those hard-to-reach sources. Meanwhile, the interviewed journalists have also expressed concerns about Twitter's negative influence on journalism, such as its lacks in credibility and economic values (Lee, 2015).

Integrating the large and growing body of research in Twitter's impact on journalism, it is safe to say that the expectations and norms of this type of social media have brought both new opportunities and traps to journalists' works. In a nutshell, journalists have started using Twitter to (1) keep track of what is trending online (e.g., Parmelee, 2013; Rauchfleisch et al., 2017), (2) assist expanding their scope of sourcing and interviewing (e.g., Heravi & Harrower, 2016; Johnson et al., 2018; Parmelee, 2013; Van Leuven & Deprez, 2017; Von Nordheim, Boczek & Koppers, 2018), (3) self-branding (e.g., Hanusch & Bruns, 2017; Lee, 2015; Varol & Uluturk, 2020), and (4) involvement in online discussions (e.g., Verweij & Van Noort , 2014; Xu & Feng, 2014). Meanwhile, journalists have also expressed concerns that public opinions and sentiments in the Twittersphere are oftentimes distorted (e.g., Liu, 2019; Parmelee, 2013), which is likely to be one of the consequences of the echo chamber effect (Colleoni, Rozza & Arvidsson, 2014; Du & Gregory, 2016).

With the help of this line of literature, the current dissertation strives to use qualitative, in-depth interviews to make sense of the quantitative data analysis of network intermedia agenda setting (Vargo et al., 2018). Scholars have stressed that qualitative methodologies are particularly valuable "when researchers are trying to discover, rather than measure, technological influences on society that researchers might not consider" (p. 294). Moreover, in-depth interviews are particularly suitable to expand upon quantitative data analysis regarding the interplays between traditional media and Twitter, as McCracken (1988) has highlighted, in-depth interviews enable researchers to "get under the commonplace view of the activity and see how the individuals really sees and experiences it" (p. 72). Kaye (2007) also argued that in-depth interviews allow researcher to "probe for deeper meaning" (p. 143). Therefore, this dissertation first provides evidence as to (1) how the traditional media and Twitter set network agendas and (2) how the network agendas of both platforms flow between each other, from an intermedia agenda-setting perspective. Next, this dissertation further exhibits evidence of (1) how Twitter has or has not been embedded in journalists' work routines and (2) how journalists assess its impact, to provide "probe for deeper meaning" (Kaye, 2007, p. 143) behind the network intermedia agenda setting between both platforms.

The Present Dissertation

From the network intermedia agenda-setting (Network IAS) perspective (Vargo et al., 2018), this dissertation examines (1) the ways in which the newspapers and Twitter set network agendas for the issue at hand: the BLM movement, and (2) how the agendas interact with each other in terms of the intermedia agenda-setting. Because the BLM movement already serves as the first level (issue) agenda, this dissertation probes the interconnections of the two dimensions of its second level (attribute) agenda, namely, substantive attribute and affective attribute agendas. Taking the agenda-setting of political candidates as an example, McCombs et al. (2000) suggested that the substantive attribute agenda pertains to the candidates' policy, ideology, perceived qualification, and personality; while the affective attribute agenda is related to the tone or the valence of the coverage about the candidate, which could be positive, neutral, or negative. These two dimensions of attribute agenda have been extensively examined in prior agenda-setting literature (e.g., Coleman & Wu, 2010; Kiousis et al., 1999). Following this line, this dissertation probes the substantive and affective dimensions of the attribute revolving around the issue. Juxtaposing the reviewed literature, research questions 1 and 2 about the network agenda setting model were first asked:

RQ1. How did the newspapers set the substantive and affective attribute agendas for the *BlackLivesMatter* movement at the networked (i.e., third) level?

RQ2. How did Twitter set the substantive and affective attribute agendas for the *BlackLivesMatter* movement at the networked (i.e., third) level?

Furthermore, scholars have called for the examinations of "the level of redundancy necessary to create" intermedia agenda setting effect on the public (McCombs, 2014, p. 793). Heeding the call, previous studies, albeit limited, have investigated the IAS effects between the traditional and social media at the issue agenda (e.g., Guo & Vargo, 2015), substantive attribute agenda (e.g., Guo et al., 2015), affective attribute agenda (Guo et al., 2019) and combined substantive and affective attribute agenda (Su et al., 2020) levels. To follow this vein of research and to further bolster the validity of the NAS model, I propose research questions 3 through 6 to examine the intermedia agenda setting effects between both platforms in terms of the following dimensions: (1) the substantive and affective attributes, separately, (2) each substantive attribute combined with a certain affective attribute, (3) several pairs of bundled substantive attributes, based on the frequencies, and (4) several pairs of bundled substantive attributes combined with affective attributes:

RQ3: What is the intermedia agenda-setting effect between the newspapers and Twitter in terms of substantive and affective attributes, separately?

RQ4: What is the intermedia agenda-setting effect between the newspapers and Twitter in terms of each substantive attribute combined with a certain affective attribute?

RQ5: What is the intermedia agenda-setting effect between the newspapers and Twitter in terms of the bundled substantive attributes?

RQ6: What is the intermedia agenda-setting effect between the newspapers and Twitter in terms of the bundled substantive attributes combined with a certain affective attribute?

The quantitative analysis will expectedly provide a picture as to *how* both platforms set their agendas of the BLM movement at the networked level, and *which* media platform is more influential in shaping the agenda of its counterpart at different dimensions. Upon the examination the network agendas of the newspapers and Twitter and the IAS effects between both outlets in various dimensions, I am committed to furthering the understanding as to *why* the effects look like what the quantitative analysis exhibits, through qualitative in-depth interviews. In essence, I ask two sets of questions, one pertains to the ways in which the journalists use Twitter in their professional routines and published works, and another pertains to the ways in which they assess Twitter's impact on journalism – the industry they work in. Therefore, the final research questions are asked:

RQ7: How does Twitter affect the journalists' professional routines and published works?

RQ8: How do the journalists assess Twitter's impact on journalism?

CHAPTER THREE

METHODOLOGY

This dissertation builds upon a mixed methodology design combining computer-assisted content analysis and in-depth interviews to address the following queries: (1) how do newspapers and Twitter set network agendas, (2) how do the agendas of newspapers and Twitter influence each other, and (3) how does Twitter affect the journalistic works of traditional media practitioners? Social network analysis (SNA) and time-series analysis (TSA) based on content analysis were conducted to delineate the network agendas of both platforms and their IAS relationships (Guo et al., 2019; Vargo & Guo, 2017; Vargo et al., 2018; Vu et al., 2014). In-depth interviews were conducted to obtain insights into the ways in which Twitter has affected the journalistic works and the professional norms among traditional media practitioners. In-depth interview is considered suitable in obtaining "a deeper understanding of everyday practices and individuals' subjective perceptions of said practices" (Kümpel, 2019, p. 385). Procedures of both approaches are detailed below.

Computer-Assisted Content Analysis

Data Collection

Newspaper data collection. Consistent with prior IAS research (Conway et al., 2015), the following newspapers were selected: *The New York Times*, the *Washington Post*, the *Wall Street Journal*, the *USA Today*, the *Los Angeles Times*, the *Star Tribune*, and the *Boston Globe*. The determination of these publications is based on the following rationale. First, the chosen outlets are among the most circulated newspapers in the U.S. ("Top 10 U.S. newspapers by circulation", 2021). Multiple prior agenda-setting studies have constructed the media agenda by the circulation of the outlets (e.g., Conway et al., 2015; Feeley & Vincent III, 2007; Lee, Lancendorfer & Lee, 2005). The higher circulation guarantees the scope of information dissemination and the depth of penetration; therefore, highly circulated newspapers deem strong in agenda-setting. Second, the chosen newspapers present a relatively broad ideological spectrum, in which the *Wall Street Journal* was considered leaning conservative, the *USA Today* being moderate, and other publications leaning liberal (Boston University Libraries, 2020). The inclusion of media outlets with multiple partisan leanings deems imperative as it ensures that the agenda the media represent does not favor only one specific ideological camp (e.g., Vliegenthart & Walgrave, 2008). Last but not least, scholars have argued that national newspapers, such as *The NYT* and the *Post*, are significant agenda setters for both domestic and international issues (Boyle, 2001; Golan, 2006; McCombs, 2005; Vargo & Guo, 2017). The *LA Times* is "representative for the western U.S." (Conway et al., 2015, p. 367; Towner & Muñoz, 2020). The *USA Today* "targets the more general reader who has some interest in politics" (Towner & Muñoz, 2020, p. 5). Taken together, a considerable size of agenda-setting research has utilized these newspapers to constitute the media agenda in various contexts (e.g., Conway et al., 2015; Kim et al., 2016; Towner & Muñoz, 2020). The determination of these outlets for this dissertation aligns with prior literature.

Next, samples were downloaded through two extensively employed databases, LexisNexis and Pro Quest (Towner & Muñoz, 2020). "BlackLivesMatter OR Black Lives Matter OR BLM" were utilized as keywords to retrieve news articles published from May 25 through

November 3, 2020. The determination of this time frame is based on the following rationale. In practical terms, May 25th is the date of George Floyd's death, which ignited the subsequent BLM demonstrations. November 3rd is the 2020 Presidential Election day, which is selected in that, according to pundits and scholars, the months-long BLM movements (1) could reshape the outcome of the election (Alter, 2020), and (2) both mainstream media and Twitter users have switched their attention and focused more on the election itself starting that day. In theoretical terms, decades of IAS scholars have indicated that the optimal span to identify IAS effects was four weeks or longer (e.g., Fernando, Suganthi, & Sivakumaran, 2014; Roberts & McCombs, 1994; Vliegenthart & Walgrave, 2008; Winter & Eyal, 1981). Therefore, this time frame is considered appropriate.

The collected samples consisted of newspapers of both their print and online versions, which will represent a discourse that is widely accessible to the general public. The initial search has generated 6,020 articles. Next, the data cleaning was proceeded in two phases. First, using the duplication removal functionalities of the databases, duplications were removed. Second, two graduate students screened the full sample and manually removed advertisements, corrections, editorials, and contents irrelevant to the topic of interest, yielding 5,630 newspaper articles in total (N_{NYT} = 1,435, $N_{The\ Post}$ = 1,524, N_{WSJ} = 516, $N_{USA\ Today}$ = 895, $N_{LA\ Times}$ = 541, N_{BG} = 590, N_{ST} = 129).

Twitter data collection. Tweets were retrieved from public Twitter accounts through the Twitter streaming application programming interface (API). The exact same keywords for the newspaper sampling, and hashtags of the exact same keywords (e.g., #BLM), were used to harvest tweets. It bears mentioning that during the high-traffic periods, such as when the news of George Floyd's death was first reported, the API "automatically limited the rate of tweets sent via the API" (Vargo et al., 2014, p. 302). As a result, 2,021,776 tweets were downloaded. A Python script was developed to remove duplicates, tweets in languages other than English, and tweets that only contained hashtags or links without texts, which returned 1,743,012 valid tweets with substantial contents.

Coding Instrument

Substantive attributes. To generate substantive attributes, an unsupervised machine-learning (UML) approach, Latent Dirichlet Allocation (LDA)-based topic modeling, was applied. The LDA is "an advanced statistical tool for the automatic discovery and comprehension of latent thematic structure or topics" (Guo, 2019, p. 2466), which has been used extensively for topic modeling (e.g., Su et al., 2020; Xue et al., 2020). A Python package "*Gensim*" was utilized to train the model. The LDA analysis has returned 20 main "topics" and the probabilities of all terms associated with each topic. Figure 1 shows the inter-topic distance map via multi-dimensional scaling. As can be seen in Figure 1, each circle represents a "topic" detected by LDA. The bars at the right side represents the top words associated with each topic. All topics have been assigned a name according to the top terms associated. For instance, as Figure 1 shows, terms "coronavirus," "health," "pandemic" and so on constituted topic 7, this topic was further named "COVID-19."

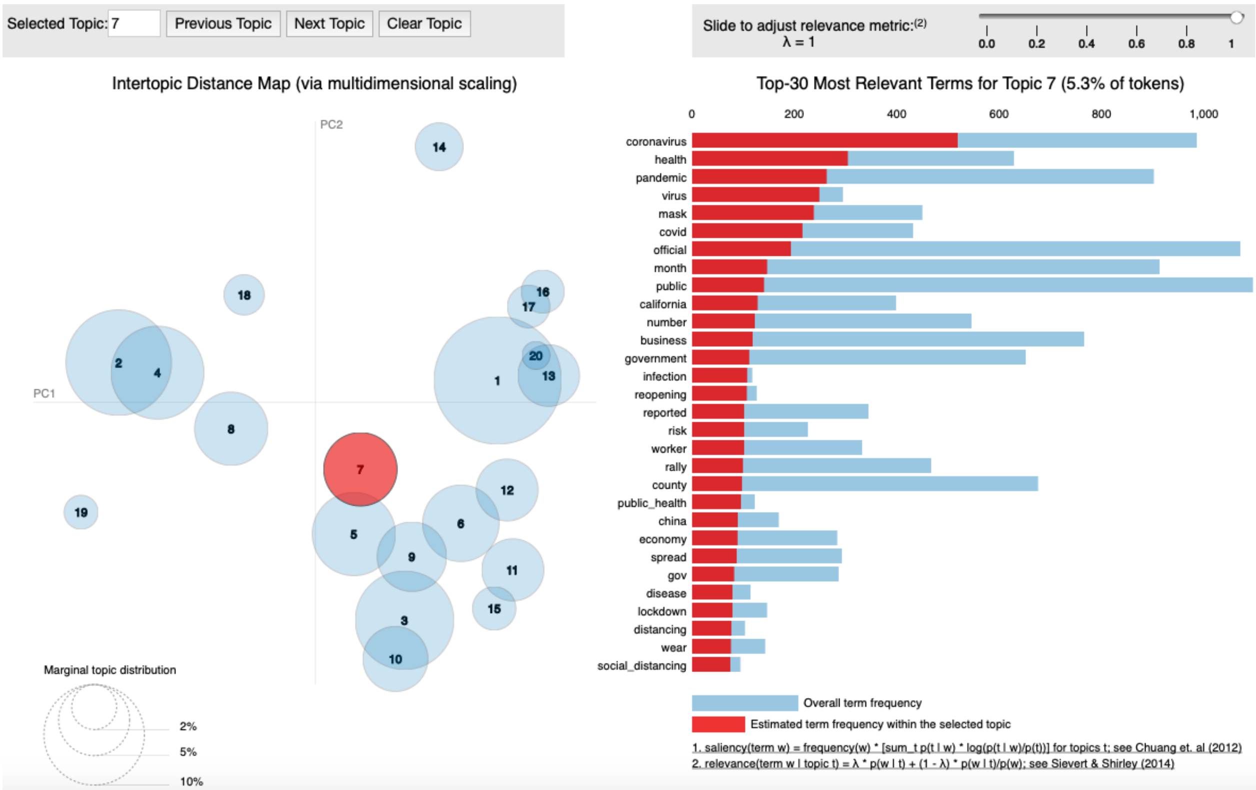

Figure 1. Inter-topic distance map via multi-dimensional scaling generated by unsupervised machine- learning topic modeling (topic 1 as an example).

Although the topics were largely independent, several overlaps can be observed, suggesting relatively higher extents of topical homogeneity. For instance, topics 2 and 4 are overlapped (see Figure 1). A closer read of the top terms associated with each respective topic revealed that both topics pertain to police and policing, hence, these two words were combined as one. Similarly, in light of the overlap across topics 1, 13 and 20, which all pertain to the killing of George Floyd, they were combined as a same topic. As a result, 16 topics were generated, which were treated as the substantive attribute agendas of the issue. Table 1 shows a full list of the substantive attributes, the top terms associated with each attribute, and tokens of these substantive attributes.

Table 1. *Substantive attributes generated by LDA-based topic-modeling*

Top 20 terms associated with each topic	Substantive attributes	Tokens
Officer, Minneapolis, video, mr_floyd, police_officer, crowd, shooting, killed, arrested, Louisville, killing, arrest, incident, Chauvin, black_man, neck, breath, knee, knee_on, brutality	Killing of Floyd	16.1%
Biden, voter, election, vote, party, mr_trump, campaign, voting, ballot, poll, candidate, race, politics, presidential, convention, political, joe, national, primary, electoral	The 2020 Election	11%
federal, washington, mayor, bowser, square, church, law, military, demonstrator, Saturday, Lafayette, Lafayette_square, violence, enforcement, district, force, guard, front, outside, parade	Demonstrations & Protests	9.6%
policing, law, community, force, reform, police_department, bill, council, public, district, legislation, enforcement, budget, law_enforcement, mayor, justice, leader, police_officer, federal, policy	Police & Policing	8.5%
coronavirus, health, pandemic, virus, mask, covid, number, infection, reopening, reported, risk, worker, public_health, china, spread, disease, lockdown, distancing, wear, social_distancing	COVID-19[1]	6.8%
violence, antifa, officer, law, movement, crime, law_enforcement, activist, looting, Portland, armed, gun, anti, justice, nypd, violent, gas, tear_gas, stick, shooting	Violence	5.8%
racial, race, racism, systemic, movement, civil, leader, civil_right, American, discrimination, racist, white_supremacy, voter, African_american, black, matter, response, killing, equity, response	Systemic Racism	5.3%
house, republican, democrat, romney, administration, plan, federal, campaign, democratic, gop, official, party, Washington, scott, advisor, congress, senate, admin, senator, establishment	American Politics	5.3%
company, employee, executive, fund, brand, business, amazon, technology, service, organization, donation, bank, industry, recognition, program, sale, license, firm, unemployed, jobs	Economy	4.8%
School, student, university, child, education, problem, teacher, close, shut, children, learning, son, pedagogy, owner, response, college, teach, class, schooling, tuition	Schooling & Education	4.2%

[1] A closer read of the sample suggested that COVID-19 here refers to the pandemic situation associated with the BLM movement; hence, it is treated as a substantive dimension of the chosen issue.

Cancel, statue, confederate, flag, removed, monument, banned, remove, symbol, virginia, public, canceled, figure, revolution, king, removal, memorial, legacy, cancel_culture, ban	Cancel Culture	3.8%
justice, court, former, attorney, decision, immigration, freedom, general, love, kamala_harris, legal, litigate, illegal, bill, code, commitment, decree, edict, lawyer, constitution	Justice & Legal System	3.8%
polarization, polarized, affective, divided, divide, radical, righteous, conflict, left, leftist, alt_right, partisan, imaginary, communist, communism, extreme, hypocrites, ideological, alternative, divisive	Political Polarization	3.8%
museum, art, artist, court, century, painting, exhibition, image, statue, institution, collection, gallery, Kaepernick, author, novel, league, album, taylor_swift, social	Culture & Arts	1.8%
facebook, medium, media, social, social_media, tiktok, twitter, tweet, app, posted, comment, Zuckerberg, online, network, content, user, video, information, account, page	Social Media	1.8%
reaction, condemn, BLM, France, united_nations, berlin, France, Germany, latino, public, international, global, America, reaction, coverage, press, Belgium, London, globe, backlash	International Response	1.6%

It merits noticing that, since the analyzed samples were all media coverage on and tweets about the BLM movement, those containing discussions on COVID-19 pertained to the association between the pandemic and the BLM. Examples could be a coverage of *The Post* entitled "Activists halt street protests in South Carolina as some demonstrators become infected" and an article in the *Chicago Tribune* entitled "How much did protests spread COVID-19 in Chicago? No way to know for sure, but overall figures continue to trend downward." Many Twitter users have also discussed this substantive aspect (i.e., the COVID-19) of the BLM movement. For instance, a tweet read "*Su[r]prise, surprise in the wake of all the mass protests the death toll climbs again after cases surge in sunbelt states. BLM movement helping COVID-19 spread death to the BAME community!*" is a manifestation about how the users discussed about this dimension of the activity. As these samples pertained to the pandemic *amid* the movement, COVID-19 is treated as a substantive attribute of the issue.

The NAS model argues that the media are able to connect various elements and transfer the network to the public. Therefore, consistent with the traditional art of methodology of the NAS research (e.g., Kiousis et al., 2016; Kiousis & Ragas, 2015; Wu & Guo, 2020), substantive attributes were not treated as mutually exclusive, instead, at least two substantive attributes in a single article were coded. For example, in an article of *The Post* entitled "How the coronavirus pandemic helped the protests become the biggest in U.S. history," "demonstrations & protests" and "COVID-19" were both coded. All substantive attributes were dummy coded (0 = absent, 1 = present).

Affective attributes. Affective attribute agendas were operationalized as the valence used in the coverage/discussions on the issue and were coded on a 5-point scale (1 = extremely condemning, 2 = condemning, 3 = neutral/mixed, 4 = supportive, 5 = extremely supportive). In other words, if a newspaper article or a tweet discussed about the BLM movements in an extremely supportive tone, it was coded as 5, so on and so forth.

The affective attributes were coded with gradient colors using Python. Specifically, a color spectrum was created to visualize the extent of affective attributes. In other words, if a unit of analysis was coded as 1 (extremely condemning to the BLM movement), it will be represented by dark red in the NAS model visualization. Light red is applied to represent 2 (condemning), grey for 3 (neutral/mixed), light blue for 4 (supportive), and dark blue for 5 (extremely supportive).

This coding strategy is anchored by prior research (e.g., McCombs et al., 1997; Su et al., 2020), which divided the affective attributes into three broad categories (i.e., positive, neutral, negative), but it made advancement. Admittedly, the either-or situation is not applicable to all of the coverage and tweets. A coverage can be moderately supportive, using an overall supportive valence while still covering some dark sides. This situation is more likely especially considering the journalistic principle of balance by which media practitioners are committed to abiding (Lacy, Fico & Simon, 1991; Lewandowsky, Ecker, Seifert, Schwarz, & Cook, 2012). It is also the case in Twittersphere, where uncondemning posts do not necessarily mean to be neutral or supportive (Hoover et al., 2020; Yoo, Brown & Chung, 2018); some of them were largely moderately supportive or mildly condemning. Therefore, the three-category technique in the previous research seems inadequate in representing the nuanced valences in the news coverage and public opinions. Through using a 5-point Likert scale to code the affective attribute agenda, this dissertation also heeds the scholarly call as to "calculate a valence scale" for affective attributes as an alternative to the conventional dummy-coding strategy (Su et al., 2020, p. 19).

Coding by Supervised Machine-Learning

A Supervised machine-leaning (SML) approach is used to code the sample. As previous scholars have suggested, the traditional manual-coding-based content analyses have multiple drawbacks such as time-, money- and effort-consuming (Pilny et al., 2019), as well as the subjectivity of manual processing, (Matthes & Kohring, 2008). SML is an effective approach when researchers "have input variables (*X*) and an output variable (*Y*) and…use an algorithm to learn the mapping function from the input to the output" (Brownlee, 2016, p. 16). It is called supervised machine-learning because the process of an algorithm learning from the training dataset "can be thought of as a teacher supervising the learning process of the machine" (Brownleee, 2016, p. 16; Pilny et al., 2019).

The coding instrument includes two variables: (1) substantive attributes (topics returned by the LDA-based topic modeling) and (2) affective attributes. The substantive attributes were dummy coded (0 = absent, 1 = present), while the affective attributes were coded based on the 5-point Likert scale (1 = extremely condemning, 5 = extremely supportive). The unit of analysis is an individual article and a tweet. Since the substantive attributes were not treated as mutually exclusive, the co-occurrence of different substantive attributes in one unit of analysis are reflected as “edges” between each “node” in the semantic networks.

Manual annotation. Manual annotation was conducted to prepare the material for the Support Vector Machine (SVM) algorithm training (Guo, 2019; Wang & Guo, 2018). Manual annotation is a pre-step for training the algorithm. Specifically, I first manually coded a subsample of data. Next, I used these manually coded sample to train the algorithm, supervising the latter to understand how the data should be coded, such that the algorithm will code the rest of the samples based on what it has learned from the manually coded sample (Cole-Lewis et al., 2015). This manual coding process is regarded “manual annotation” of SML-assisted coding (Scharkow, 2011, p. 769).

The following steps for manual annotation have been taken. First, two sets of random samples have been selected from the full datasets of newspaper and Twitter, respectively. As a result, 1,200 newspaper articles and 4,000 tweets were captured from the datasets of both media platforms, respectively. Second, ten percent of data from each respective random sample were further generated ($N_{Newspaper} = 120$ $N_{tweets} = 400$) for intercoder reliability test. Specifically, based on the coding instruments for substantive and affective attributes, two trained coders coded all these 120 newspaper articles and 400 tweets independently, then met and discussed the least agreed variables. Upon discussion, both coders recoded all the randomly selected samples again. The intercoder reliability alphas for the substantive attributes reached .79 or higher, the alphas for affective attributes reached .83, which were considered satisfactory (Krippendorff, 1980).

Finally, the researcher manually annotated the 1,200 newspaper articles and 4,000 tweets, which were used as the material for the SVM algorithm training.

SVM algorithm training. As stated earlier, upon completion of the manual-annotation process, the manually annotated sample will be used to train the algorithm and teach the latter to understand the ways in which the data should be coded (Brownlee, 2016). A pretest of the SML model performance was proceeded in the following phases. First, following previous network IAS research (e.g., Wang & Guo, 2018), both manually annotated random samples have been divided into two categories: a "training set" (70% of the sample) and a "testing set" (30% of the sample), respectively. As a result, for the newspapers' random sample, 840 manually annotated articles were assigned into the "training set" and 360 into the "testing set;" for the Twitter sample, 2,700 manually annotated tweets were assigned into the "training set" and 1,300 into the "testing set." Second, a Python script was written to train the SVM using both training sets (see Appendix A). In essence, the algorithm was commanded to screen the manually annotated training sets as a process of machine-learning (Wang & Guo, 2018). Upon completion, the algorithm acquired the coding methodology and pattern through screening how the researcher has annotated the samples. Finally, the trained algorithm was used to independently code both testing sets. Upon completion, the "testing sets" coded by the SVM algorithm and the same 30% of manually annotated samples were compared. Specifically, the false positives, false negatives and *F* scores of all variables were calculated to examine the algorithm performance. Table 2 represents the model performance of the SVM algorithm. As can be seen in the Table, the precision score, recall and *F* scores for all variables have reached .70 or higher, suggesting a satisfactory performance (Meyer, Leisch & Hornik, 2003). Therefore, the trained algorithm is safe to be used to detect and code the rest of the corpus.

Table 2. Model performance of supervised machine-learning.

Attribute Agendas	Newspapers			Twitter		
	Precision	Recall	*F*-score	Precision	Recall	*F*-score
Substantive attributes						
Killing of Floyd	.747	.715	.725	.994	.981	.986
The 2020 Election	.917	.861	.882	.986	.919	.946
Demonstration & Protest	.884	.746	.790	.916	.850	.869
Policing & Police	.771	.722	.727	.943	.928	.933
COVID-19	.870	.793	.819	.995	.947	.968
Violence	.801	.719	.743	.879	.814	.832
Systemic racism	.769	.705	.727	.879	.836	.850
American politics	.901	.864	.875	.941	.819	.865
Economy	.927	.820	.850	.961	.881	.910
Schooling & Education	.969	.919	.936	.99	.972	.986
Civic movement	.972	.939	.950	.995	.903	.944
Justice & legal system	.872	.831	.845	.987	.844	.904
Political polarization	.997	.936	.964	.952	.900	.917
Culture & arts	.851	.837	.842	.997	.883	.935
Social media	.956	.827	.875	.962	.906	.926
International responses	.998	.939	.969	1.00	.914	.955
Affective attributes	.979	.820	.957	.729	.704	.729.

Notes: Precision: the ratio of true positives to the total predicted positive observations. Recall: the ratio of true positives to all observations in the actual case. *F*-score: the weighted average of prediction and recall.

Real coding. The trained SVM algorithm was used to code the full sample. As previously suggested, to fit the NAS model, which highlights the transfer of the interconnections across elements, a unit of analysis should contain two or more substantive attributes (Guo, 2011; Guo et al., 2015; Guo et al., 2019; Guo & Vargo, 2015; Vu & Guo, 2014). Therefore, the SVM algorithm was commanded to code at least two substantive attributes for each unit of analysis and remove those containing less than two. As a result, 1,237,537 tweets and 4,189 newspaper articles were identified as valid samples that contain at least two substantive attributes, denoting the ability to interconnect various elements in one unit of analysis. These samples constituted the final valid samples of the current dissertation.

Analytical Strategies for Content Analysis

Upon completion of coding, this dissertation utilizes two approaches for the content analyses. Social network analysis is performed to reveal the network agendas of the newspapers and Twitter. Time-series analysis is conducted to examine the IAS effects between the network agendas of the newspapers and that of Twitter.

Social network analysis. The *R* package "*igraph*" is used to visualize the semantic networks of the media agenda and the discussions on Twitter. In each semantic network, the size of a node represents the frequency the given node is covered. In other words, the larger a node, the more frequently the given substantive attribute has occurred, and vice versa. Likewise, the thickness of an edge represents the frequency of the co-occurrence of the bridged nodes. In other words, the thicker an edge, the more frequently the bridged substantive attributes co-occurred in the agendas, and vice versa. When it comes to the affective attributes, the color depths of nodes represent the strength of the affective attribute associated with a specific substantive attribute.

For instance, a node in dark blue represents a substantive attribute that has more frequently been depicted in a strongly supportive valence, while a node in slight blue represents a substantive attribute that have more often been depicted in a moderately supportive valence, and vice versa. Given that the affective attribute is coded on a 5-point Liker scale (1 = extremely condemning, 5 = extremely supportive), when visualizing the network agendas, each node is assigned an average affective-attribute score. As a result, nodes will be represented in gradient colors in the network visualizations.

Time series analysis. When it comes to the time-series analysis, Granger causality tests were conducted to inspect the intermedia agenda-setting effects between both platforms (Granger, 1969). Granger causality test is one of the most commonly used techniques in the IAS research (e.g., Guo et al., 2019; Meraz, 2011). Granger causality test is a statistical test for determining causal inferences between various time-series data, namely, whether one time-series is able to forecast another (Granger, 1969). In addition to its ability to investigate predictive causality (Diebold, 2004), Granger causality test is also useful in detecting revealing precedence (Leamer, 1985). In other words, Granger causality tests can not only show whether one time-series causes its counterpart, it can also exhibit whether one time-series is able to forecast its counterpart (Hamilton, 1994). Moreover, according to Meraz (2011), the application of Granger causality tests to IAS research permits "predictions of each media network's agenda based on the lagged values of its past agenda and those of other media networks." (p. 182). Therefore, Granger causality test, the conventional art of examination of IAS effects, is appropriate to be used in this dissertation.

Prior to performing the Granger causality tests, two steps were taken as preliminary analyses. First, data stationarity is checked because Granger causality tests require that time-series data achieve stationary or “consistency in statistical parameters (e.g., mean, variance, autocorrelation) over time” (Billard, 2019, p. 169). Stationarity refers to the statistical properties of a process generating a time series that do not change over time (Vlahogianni, Karlaftis, & Golias, 2006). Consistent with previous IAS research (e.g., Billard, 2019; Guo, 2019; Tan & Weaver, 2013; Vliegenthart & Walgrave, 2008), augmented Dickey-Fuller (ADF) test is used for each individual attribute series to testify the stationarity of the overall data (Fuller, 2009; Vliegenthart & Walgrave, 2008).

Next, pre-whitening time-series is further performed to remove the possibility of agenda convergence. Specifically, scholars argued that newspaper coverage and tweets can display common internal cycles, and such random correlations could be mistakenly identified as causal inferences (Zheng & Mita, 2007). Therefore, an Autoregressive–moving-average (ARMA) model is determined to remove this possibility. Scholars have suggested that the ARMA model is able to provide a parsimonious description of a stationary stochastic process (Brockwell & Davis, 1987) and “further connections between stationary long memory processes and non-stationary models” (Samorodnitsky, 2006, p. 179). According to Zheng and Mita (2007), “ARMA models are often applied to time-series representation” and “is able to represent the safe state” (p. 1830). A large number of IAS studies have used ARMA models for pre-whitening, minimizing the chances of agenda convergence while guaranteeing the causal inferences (e.g., Kim et al., 2016; Trumbo, 1995; Wells et al., 2019). The pre-whitening is proceeded in the following two phases. Initially, using Python, I estimated a time-series model for the newspaper sample by an ARMA model and stored the residuals. Next, I filtered the Twitter series using the above model. The detailed procedures of both the ADF test and the pre-whitening time-series can be found in Appendix A.

Upon completion of both the ADF test and the pre-whitening time-series, Granger-causality tests were conducted between the residuals from the first step and the filtered Twitter series from the second step to predict the intermedia agenda-setting effects across the newspaper agenda and Twitter agenda.

One single day is used as the time lag in the model. The determination of this daily basis is based on the following rationale. First, all the chosen newspapers publish on a daily basis. Second, scholars have suggested that media's agenda-setting can effectuate from one day to one week (Vargo et al., 2015). Third, Haim, Weimann and Brosius (2018) suggested that one day represents a conservative lag, "which is most likely not subject to overestimating any effects" (p. 281). Therefore, consistent with previous IAS studies (e.g., Guo et al., 2019; Haim et al., 2018; Meraz, 2011; Vonbun et al., 2016), this dissertation uses one day as the time lag.

In-depth Interviews

In-depth interview is a conventional qualitative research methodology used to collect direct, one-on-one interview data. Scholars argued that qualitative methodologies, including in-depth interviews, “let the researcher understand and present the world as it is seen and experienced by the participants without predetermining those standpoints” (Yilmaz, 2013, p. 313). In-depth interviews are also used in a mixed-methodology context, helping researchers make sense of the quantitative data analysis and is particularly valuable “for providing information and background on issues that cannot be observed or efficiently accessed” (Tracy 2013, p. 132). The approach of in-depth interviews with journalists is particularly utilized by researchers investigating the mutual influences between social media and journalism (e.g., Canter, 2015; Parmelee, 2014; Powers & Vera-Zambrano, 2018). For instance, in understanding how the political tweets have shaped newspaper coverage of the 2012 U.S. Presidential Election campaign, Parmelee (2014) conducted in-depth interviews with 11 political reporters and editors at U.S. newspapers. Boczek and Koppers (2020) conducted in-depth interviews with journalists to understand how the utilization of WhatsApp among journalists influenced their journalistic routines.

To elucidate the motives of journalists in agenda-setting and their perceptions of Twitter’s impact on their professional works, qualitative in-depth interviews were conducted. Participants were interviewed individually via telephone calls and zoom video calls and were encouraged to elaborate interview statements that reflected the complexities of their thought processes (Bartsch, et al., 2016).

Participants and Procedure

Participants were journalists in the chosen media. Participants were recruited through personal contacts, such as emails, of the researcher but were not personally known to the researcher. The researcher has sent out 114 invitations from Jan 15 through Feb 10, 2021, as a result, seven journalists agreed to participate in the interview, lending a response rate of 6.14%. This sample size, though limited, is similar to previous mixed-method studies, which utilized in-depth interviews with journalists to make sense of the quantitative data analyses (e.g., Parmelee, 2014; Tandoc Jr & Foo, 2018).

All interviewees received a 25-dollar gift card as incentive in return for their participation. Once the contacted journalists agreed to be interviewed, they were informed about the interview process through an email sent from the researcher, with regards to recording, transcription, anonymization, and confidentiality (Bartsch, et al., 2016). Next, the participants were asked to complete a short questionnaire enclosed in the email, including a consent form in the first page, their contact information in the following page, as well as an item asking for their preferred format of interview (i.e., dialing and zooming). Upon completion of the short online questionnaire, the in-depth interviews have been performed at the scheduled times via telephone or zoom, according to their preferences. At the beginning of the phone calls and zoom video calls, the researcher elaborated on the research background and purpose again before asking the semi-structured interview questions.

Interview Guideline

The semi-structured interview guideline consisted of a series of close-ended and open-ended questions about the interviewees' perceptions of Twitter's impact on their work routines, published works and professional norms, and their insights into the pros and cons of Twitter's impact on the industry and journalistic norms. The interview guideline has not been implemented without strict adherence to the order of questions, "in order to facilitate a natural flow of recall and elaboration" (Bartsch, et al., 2016, p. 748).

The interview started with a series of close-ended questions. Initially, the interviewees were asked whether they use Twitter, and if so, for what purposes. Then, the interviewees were asked to detail whether they read Twitter news feed pertaining to the issue before writing their own stories. Further, the following three open-ended questions were asked: (1) How has Twitter changed your work routines and your published works? (2) How has Twitter changed the professional norms in the news industry? And (3) How do you evaluate the pros and cons of Twitter's impact on traditional journalism, respectively?

The interviews lasted 25 – 35 minutes and were conducted between January and February 2021. As with prior in-depth interview research (e.g., Tandoc Jr & Foo, 2018), the interviews were transcribed verbatim. I independently read and coded each of the transcript, categorized the coded transcript, and grouped the categories "into larger conceptual bins," which is helpful in providing examples from the data (Bartsch, et al., 2016; Tandoc Jr & Foo, 2018, p. 45).

CHAPTER FOUR

RESULTS

Data Analysis

RQ1 asked about the ways in which the newspapers depict the substantive and affective attributes of the BLM movement at the networked level. This dissertation seeks to address this research question in three aspects. (1) This dissertation first examines the ways in which the newspapers set the substantive attribute agenda independently, through inspecting the sizes of nodes. (2) It further examines the ways in which the newspapers bundled the substantive attributes and affective attributes, through investigating the colors assigned to the nodes. (3) Finally, it examines the ways in which the newspapers bundled all the substantive attributes, through exploring the edges that bridged the nodes.

The *R* package *igraph* was used to delineate the network agendas. In terms of the saliencies of the substantive attributes, the size of a node represents the saliency the newspapers have placed on its agenda. In other words, the larger a node, the more frequently the given substantive attributed has been covered in the newspapers. As can be seen in Figure 2, "police & policing" was the most covered substantive attribute in the newspapers' agenda, followed by "killing of Floyd," "American politics," "violence," and "systemic racism." The least covered substantive attributes are "international response," "polarization," "cancel culture," and "schooling & education." Table 3 exhibits the descriptive statistics of all the network agenda (i.e., frequencies of the substantive attributes and average scores of the affective attributes associated with the substantive attributes).

In terms of affective attributes, the darkness of color represents the valence (i.e., affective attributes associated with each substantive attribute). The 5-point Likert scale was visualized by a gradient color spectrum, in which dark red represents the extremely oppositional valence (i.e., 1) while dark blue represents the extremely supportive valence (i.e., 5). Similarly, the decrease in the color density denotes the decrease in the valence intensity; hence, the color of grey represents the most neutral valence. As Figure 2 shows, all substantive attributes in the newspapers' agenda have been depicted with a supportive valence but in nuanced densities. Integrating Figure 2 and Table 3, it is inferred that the substantive attribute of "polarization" was depicted with the strongest supportive valence ($M = 4.012$) among all other substantive attributes. In other words, among the BLM-related newspaper reports, the coverage is more likely to have a supportive attitude toward the movement when the coverage is mentioning the issue of ideological polarization. The substantive attribute with the second strongest supportive valence was "systemic racism" ($M = 4.010$), suggesting that the substantive aspect of systemic racism in the BLM movement was also associated with a more supportive tone in the related newspaper coverage. The substantive attribute with the weakest supportive valence were "culture & arts" ($M = 3.921$), "international response" ($M = 3.934$) and "COVID-19" ($M = 3.934$). This suggests that the newspaper reports were more likely to tend to be relatively neutral when it comes to these substantive aspects of the BLM movement. This is quite reasonable as compared with substantive attributes such as systemic racism or killing of Floyd, which have caused outcry within the country, these three topics have a weaker relationship with domestic politics and ideological issues. On the contrary, the substantive attributes of culture and arts, COVID-19 and international response are either unconfined in the context of the U.S. or more depoliticized. Therefore, it is not likely to cause more extreme emotional expressions. However, it is still noticeable that although all substantive attributes were depicted with different extents of affective attributes, the differences in affective attributes are rather minimal; the largest difference is only 0.09. This indicates that when newspapers portray different aspects of the BLM movement, their basic stands and affective attitudes are stable and homogeneous rather than disparate and heterogeneous.

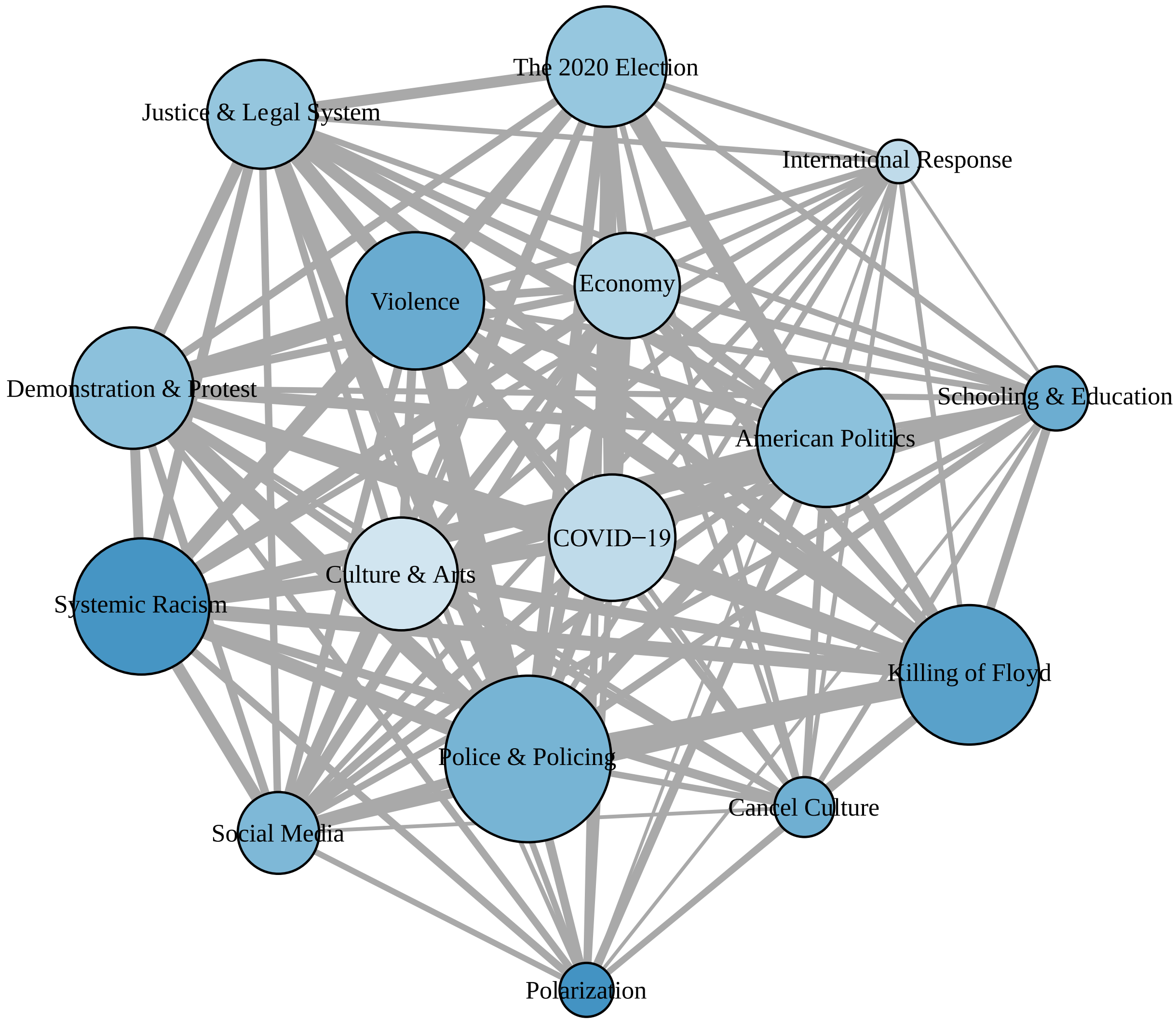

Figure 2. *Network agenda of newspaper coverage on the BLM movement.*

Table 3. Descriptive statistics of the network agendas of the newspapers.

Substantive attributes	Newspapers: Average score of Affective attributes	Newspapers: Number of Substantive attributes
Killing of Floyd	3.99835	1212
The 2020 Election	3.9629631	891
Demonstration & Protest	3.969163	908
Police & Policing	3.981164	1752
COVID-19	3.934144	987
Violence	3.989787	1175
Systemic Racism	4.009565	1150
American Politics	3.969874	1195
Economy	3.945347	677
Schooling & Education	3.987448	239
Cancel Culture	3.985577	208
Justice & Legal System	3.964187	726
Polarization	4.011976	167
Culture & Arts	3.920716	782
Social Media	3.977330	397
International Response	3.933962	106

Note. the scores for affective attributes average scores based on the 5-point Likert scale (1 = extremely oppositional, 5 = extremely supportive).

In addition to (1) how the newspapers set agendas of substantive attributes, and (2) how they associated the affective attributes with the substantive attributes, this dissertation further explores how the newspapers bundled each substantive attribute. Integrating Figure 2 and Table 4, it is shown that the substantive attributes of "police & policing" and "violence" were associated with the most edges, which indicates that both substantive attributes have been frequently mentioned together in a newspaper coverage. A closer read of the samples revealed that numerous coverages have devoted to the depictions of police brutality. One of the exemplars could be a report in the *USA Today* entitled “Seattle officer on leave after video shows cop rolling bicycle over protester's head”, which states that:

> *While protesters mostly retreated, a person who appeared to be wearing head protection can be seen lying in the street. As officers on bikes moved forward, one officer who was walking beside his bike can be seen rolling the bike over the head or neck of the person lying in the street* (Shannon, 2020).

Moreover, pairs such as “killing of Floyd” and “police & policing,” “demonstration & protest” and “police & policing,” and “the 2020 election” and “American politics” also co-occurred frequently, which are also reflected in the thick edges between the respective nodes, as can be seen in Figure 2.

In a nutshell, the newspapers have depicted various aspects of the BLM issue with a moderately supportive valence and have placed particular saliencies on the substantive attributes of “police & policing,” “killing of Floyd,” “American politics,” “violence,” and “systemic racism.” Moreover, a majority of coverage has bundled “police & policing” and “violence” among others.

Table 4. Descriptive statistics of the edges in the network agenda of the newspapers.

Substantive Attribute 1	Substantive Attribute 2	Number of Edge
Killing of Floyd	The 2020 Election	108
Killing of Floyd	Demonstration & Protest	440
Killing of Floyd	Police & Policing	849
Killing of Floyd	COVID-19	131
Killing of Floyd	Violence	557
Killing of Floyd	Systemic Racism	321
Killing of Floyd	American Politics	181
Killing of Floyd	Economy	137
Killing of Floyd	Schooling & Education	67
Killing of Floyd	Cancel Culture	68
Killing of Floyd	Justice & Legal System	220
Killing of Floyd	Polarization	24
Killing of Floyd	Culture & Arts	163
Killing of Floyd	Social Media	83
Killing of Floyd	International Response	12
The 2020 Election	Demonstration & Protest	44
The 2020 Election	Police & Policing	127
The 2020 Election	COVID-19	379
The 2020 Election	Violence	106
The 2020 Election	Systemic Racism	165
The 2020 Election	American Politics	687
The 2020 Election	Economy	67
The 2020 Election	Schooling & Education	20
The 2020 Election	Cancel Culture	20
The 2020 Election	Justice & Legal System	124
The 2020 Election	Polarization	41
The 2020 Election	Culture & Arts	25
The 2020 Election	Social Media	46
The 2020 Election	International Response	16
Demonstration & Protest	Police & Policing	700
Demonstration & Protest	COVID-19	86
Demonstration & Protest	Violence	551
Demonstration & Protest	Systemic Racism	95
Demonstration & Protest	American Politics	146
Demonstration & Protest	Economy	51
Demonstration & Protest	Schooling & Education	18
Demonstration & Protest	Cancel Culture	17

Demonstration & Protest	Justice & Legal System	183
Demonstration & Protest	Polarization	35
Demonstration & Protest	Culture & Arts	65
Demonstration & Protest	Social Media	53
Demonstration & Protest	International Response	26
Police & Policing	COVID-19	130
Police & Policing	Violence	1019
Police & Policing	Systemic Racism	306
Police & Policing	American Politics	276
Police & Policing	Economy	138
Police & Policing	Schooling & Education	50
Police & Policing	Cancel Culture	23
Police & Policing	Justice & Legal System	470
Police & Policing	Polarization	49
Police & Policing	Culture & Arts	164
Police & Policing	Social Media	123
Police & Policing	International Response	16
COVID-19	Violence	61
COVID-19	Systemic Racism	116
COVID-19	American Politics	414
COVID-19	Economy	252
COVID-19	Schooling & Education	55
COVID-19	Cancel Culture	16
COVID-19	Justice & Legal System	78
COVID-19	Polarization	25
COVID-19	Culture & Arts	230
COVID-19	Social Media	56
COVID-19	International Response	19
Violence	Systemic Racism	169
Violence	American Politics	217
Violence	Economy	51
Violence	Schooling & Education	23
Violence	Cancel Culture	19
Violence	Justice & Legal System	346
Violence	Polarization	51
Violence	Culture & Arts	69
Violence	Social Media	61
Violence	International Response	7
Systemic Racism	American Politics	201
Systemic Racism	Economy	240

Systemic Racism	Schooling & Education	121
Systemic Racism	Cancel Culture	69
Systemic Racism	Justice & Legal System	96
Systemic Racism	Polarization	38
Systemic Racism	Culture & Arts	292
Systemic Racism	Social Media	157
Systemic Racism	International Response	25
American Politics	Economy	122
American Politics	Schooling & Education	20
American Politics	Cancel Culture	40
American Politics	Justice & Legal System	189
American Politics	Polarization	70
American Politics	Culture & Arts	45
American Politics	Social Media	43
American Politics	International Response	20
Economy	Schooling & Education	50
Economy	Cancel Culture	15
Economy	Justice & Legal System	60
Economy	Polarization	9
Economy	Culture & Arts	120
Economy	Social Media	121
Economy	International Response	16
Schooling & Education	Cancel Culture	16
Schooling & Education	Justice & Legal System	22
Schooling & Education	Polarization	4
Schooling & Education	Culture & Arts	67
Schooling & Education	Social Media	28
Schooling & Education	International Response	3
Cancel Culture	Justice & Legal System	16
Cancel Culture	Polarization	5
Cancel Culture	Culture & Arts	43
Cancel Culture	Social Media	5
Cancel Culture	International Response	8
Justice & Legal System	Polarization	22
Justice & Legal System	Culture & Arts	38
Justice & Legal System	Social Media	37
Justice & Legal System	International Response	14
Polarization	Culture & Arts	8
Polarization	Social Media	19
Polarization	International Response	3

Culture & Arts	Social Media	89
Culture & Arts	International Response	28
Social Media	International Response	19

RQ2 inquired about the ways in which discussions on Twitter set the agenda for the substantive and affective attributes of the BLM movement at the networked level. Similarly, this dissertation seeks to address RQ2 in following three aspects. (1) This dissertation first examines the ways in which the Twitter discussions set the substantive attribute agenda independently, through gauging the sizes of nodes. (2) It further examines the ways in which the newspapers bundled the substantive attributes and affective attributes, through investigating the colors assigned to the nodes. (3) Finally, it examines the ways in which the newspapers bundled all the substantive attributes, through exploring the edges that bridged the nodes.

The *R* package *igraph* was used to delineate the network agendas of the BLM movement set by Twitter. In terms of the saliencies of the substantive attributes, the size of a node represents the saliency the Twitter users have placed on their agendas. In other words, the larger a node, the more frequently the given substantive attributed has been mentioned or discussed by the Twitter users. As can be seen in Figure 3, "violence" was the most discussed substantive attribute of the issue of BLM movement in the Twitter's agenda, followed by "police & policing," "systemic racism," and "demonstration & protest." The least discussed substantive attributes of the BLM movement among the Twitter users, as Figure 3 exhibits, are "international response," "culture & arts," and "schooling & education." Table 5 exhibits the descriptive statistics of all the network agenda (i.e., frequencies of the substantive attributes and average scores of the affective attributes associated with the substantive attributes).

Compared to the newspapers' agenda, the saliencies the Twitter users have placed on the substantive attributes did not appear to be much different. However, when it comes to affective attributes that Twitter users have applied when discussing about the BLM movement, difference has become evident. As Figure 3 displays, all substantive attributes in the Twitter's agenda have been depicted with an oppositional valence but in nuanced densities. Integrating Figure 3 and Table 5, it can be inferred that the substantive attribute of "polarization" was depicted with the strongest oppositional valence ($M = 1.075$) among all other substantive attributes. In other words, among the BLM-related discussions in Twittersphere, the discussions were more likely to have an oppositional attitude toward the movement when they mention ideological polarization. This result is opposed to the agenda of the newspapers, which have depicted the substantive attribute of polarization with the strongest supportive attribute among other substantive attributes. The substantive attribute with the second strongest supportive valence found in the Twitter's was "justice & legal system" ($M = 1.105$), suggesting that many Twitter users have emphasized and condemned the lack of legitimacy of the BLM movement and the illegal behaviors of the demonstrators. This is reflected in numerous tweets. One exemplar could be a tweet that received large number of replies:

> "*Because I disagree that BLM is identity politics. See it as a criminal justice issue. Others disagree. Your call if you want to hold a group of people responsible for the actions of a few. I'd just remind you that's what others do when they refer to the protesters as Marxists.*"

The substantive attribute with the weakest oppositional valence were "schooling & education" (M = 2.609), "international response" (M = 2.504) and "social media" (M = 2.457). The substantive attribute of "COVID-19" were also associated with a relatively neutral valence (M = 2.266), which is similar to the network agenda of the newspapers. This result also suggests that the Twitter users were more likely to tend to be relatively neutral when they discuss these substantive attributes of the BLM movement. The explication of this results is akin to that of the newspapers' agenda. Substantive attributes such as schooling, international response, social media, and COVID-19 were more of a less likely to be associated with stronger sentiments, rather, they are either unconfined to the context of the U.S. or more depoliticized.

As can be seen in Table 5, the affective attributes in the Twitter's agenda have two characteristics that merits acknowledgment. First, all substantive attributes were delineated with an oppositional valence, although nuances of the extent of attitude have emerged. Second, compared to newspapers' agenda, which has minimal differences of affective attributes across the substantive attributes, the differences of affective attributes across the substantive attributes in the Twitter's agenda is more evident. The largest difference is 1.53. This denotes that when Twitter users discuss different aspects of the BLM movement, their affective attitudes, compared to that of newspapers, are more heterogeneous and diverse.

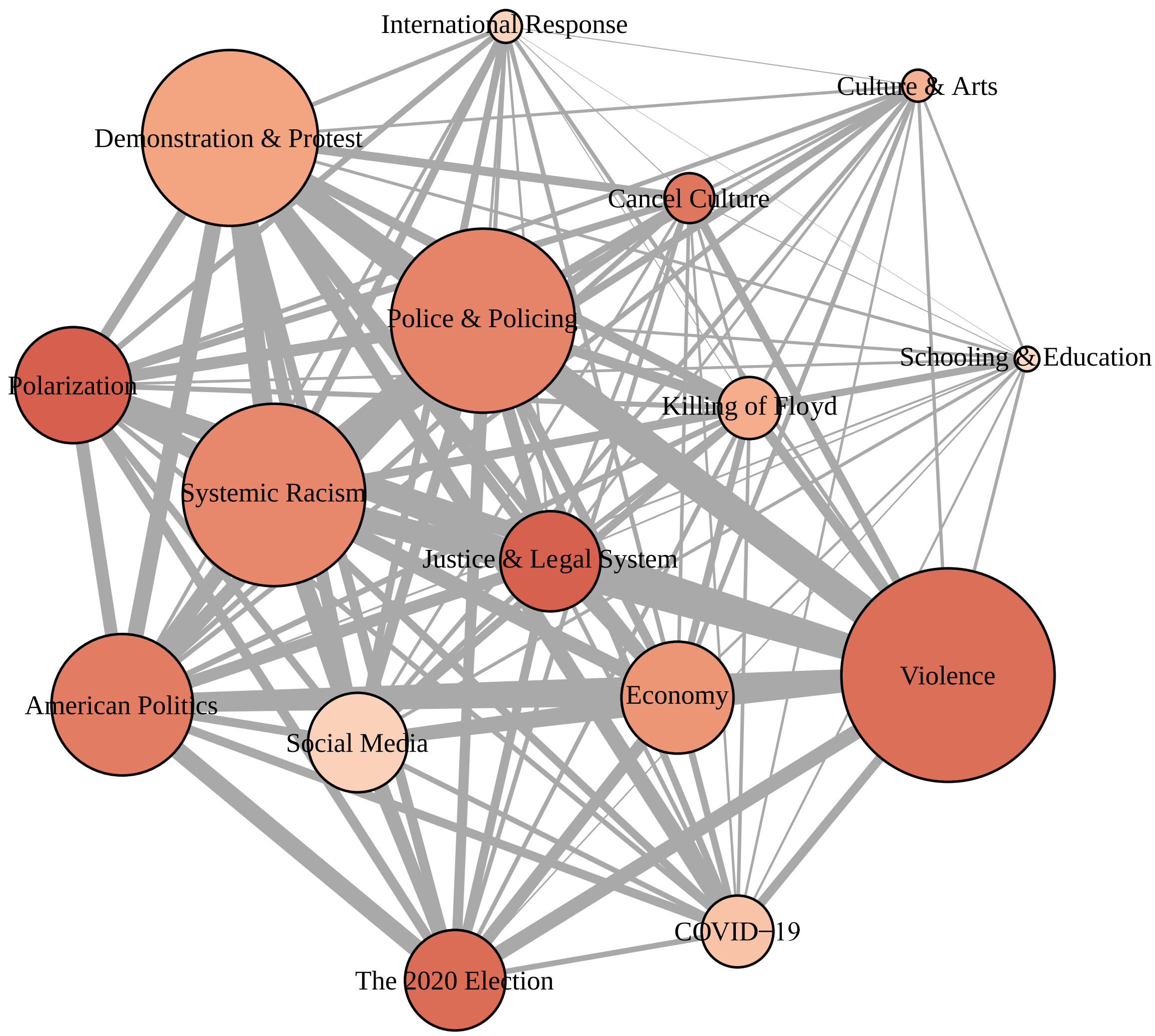

Figure 3. *Network agenda of discussion on the BLM movement in Twittersphere.*

Table 5. Descriptive statistics of the network agendas of Twitter.

	Twitter	
Substantive attributes	Average score of Affective attributes	Number of Substantive attributes
Killing of Floyd	1.961875	34151
The 2020 Election	1.216397	102178
Demonstration & Protest	1.832828	363774
Police & Policing	1.488310	402752
COVID-19	2.265867	47456
Violence	1.251503	564319
Systemic Racism	1.534001	395297
American Politics	1.409182	221960
Economy	1.679132	130256
Schooling & Education	2.608985	4207
Cancel Culture	1.325331	20619
Justice & Legal System	1.104942	101694
Polarization	1.075316	141378
Culture & Arts	2.016671	7498
Social Media	2.456929	99591
International Response	2.503796	7904

Note. the scores for affective attributes average scores based on the 5-point Likert scale (1 = extremely oppositional, 5 = extremely supportive).

In addition to (1) how the Twitter users set agendas of substantive attributes, and (2) how they associated the affective attributes with these substantive attributes, I further explore how the Twitter users bundled each substantive attribute. Integrating Figure 3 and Table 6, it is shown that the substantive attributes of "police & policing" and "violence" were associated with the most edges, which indicates that both substantive attributes have been frequently mentioned together in a newspaper coverage, reflected in the thickest edge in its network agenda (see Figure 3). A closer read of the samples revealed that numerous Twitter have devoted to the discussions of police brutality. One of the exemplars could be the following tweet:

> *"Think about how that relates to the current BLM movement. You want to protest police brutality? You'll get beat up, gassed, or shot. It's the looters' and thugs' faults. You want to defund the police? Fine, but nobody will be there to save you from murderers and rapists."*

However, different from newspapers' agenda which have applied an attitude of support to the BLM movement and condemned the police brutality, not all of the tweets were in a supportive valence to the movement. Instead, some of the tweets bundling police and violence have actually condemned the BLM movement. Instances are a tweet read "*@shrekhatesraci1 15 "unarmed" black men being shot by police in a year out of millions of interactions is not police brutality. BLM is just an excuse for people to riot, and loot*" and another tweet read "*Not our fault you escalated the BLM problem to the point that it's worse than police brutality now.*"

Moreover, pairs such as "demonstration & protest" and "violence," "violence" and "systemic racism," and "police & policing" also co-occurred frequently in the discussions of Twitter users, which are also reflected in the thick edges between the respective nodes.

In a nutshell, the Twitter users have depicted various aspects of the BLM issue in a moderately oppositional attitude and have placed particular saliencies on the substantive attributes of "violence," "police & policing," "systemic racism," and "demonstration & protests." Furthermore, a majority of these discussions has bundled "police & policing" and "violence" among others.

Table 6. Descriptive statistics of the edges in the network agenda of Twitter.

Substantive Attribute 1	Substantive Attribute 2	Number of Edge
Killing of Floyd	The 2020 Election	619
Killing of Floyd	Demonstration & Protest	8112
Killing of Floyd	Police & Policing	9420
Killing of Floyd	COVID-19	334
Killing of Floyd	Violence	8522
Killing of Floyd	Systemic Racism	5623
Killing of Floyd	American Politics	1454
Killing of Floyd	Economy	2812
Killing of Floyd	Schooling & Education	11
Killing of Floyd	Cancel Culture	214
Killing of Floyd	Justice & Legal System	1222
Killing of Floyd	Polarization	971
Killing of Floyd	Culture & Arts	133
Killing of Floyd	Social Media	3845
Killing of Floyd	International Response	8
The 2020 Election	Demonstration & Protest	7574
The 2020 Election	Police & Policing	7600
The 2020 Election	COVID-19	1234
The 2020 Election	Violence	25447
The 2020 Election	Systemic Racism	10515
The 2020 Election	American Politics	42777
The 2020 Election	Economy	13950
The 2020 Election	Schooling & Education	22
The 2020 Election	Cancel Culture	695
The 2020 Election	Justice & Legal System	5116
The 2020 Election	Polarization	7342
The 2020 Election	Culture & Arts	61
The 2020 Election	Social Media	1566
The 2020 Election	International Response	464
Demonstration & Protest	Police & Policing	93161
Demonstration & Protest	COVID-19	31263
Demonstration & Protest	Violence	154477
Demonstration & Protest	Systemic Racism	62502
Demonstration & Protest	American Politics	34353
Demonstration & Protest	Economy	7784
Demonstration & Protest	Schooling & Education	216
Demonstration & Protest	Cancel Culture	5124

Demonstration & Protest	Justice & Legal System	9209
Demonstration & Protest	Polarization	7927
Demonstration & Protest	Culture & Arts	179
Demonstration & Protest	Social Media	17086
Demonstration & Protest	International Response	742
Police & Policing	COVID-19	2658
Police & Policing	Violence	228162
Police & Policing	Systemic Racism	93241
Police & Policing	American Politics	19209
Police & Policing	Economy	6522
Police & Policing	Schooling & Education	212
Police & Policing	Cancel Culture	2136
Police & Policing	Justice & Legal System	17384
Police & Policing	Polarization	12836
Police & Policing	Culture & Arts	233
Police & Policing	Social Media	8904
Police & Policing	International Response	141
COVID-19	Violence	5938
COVID-19	Systemic Racism	3623
COVID-19	American Politics	5127
COVID-19	Economy	2407
COVID-19	Schooling & Education	81
COVID-19	Cancel Culture	100
COVID-19	Justice & Legal System	584
COVID-19	Polarization	899
COVID-19	Culture & Arts	102
COVID-19	Social Media	1054
COVID-19	International Response	100
Violence	Systemic Racism	112137
Violence	American Politics	58883
Violence	Economy	13746
Violence	Schooling & Education	243
Violence	Cancel Culture	4680
Violence	Justice & Legal System	27386
Violence	Polarization	37110
Violence	Culture & Arts	241
Violence	Social Media	9686
Violence	International Response	453
Systemic Racism	American Politics	30588
Systemic Racism	Economy	25149

Systemic Racism	Schooling & Education	2746
Systemic Racism	Cancel Culture	5673
Systemic Racism	Justice & Legal System	22876
Systemic Racism	Polarization	44602
Systemic Racism	Culture & Arts	3265
Systemic Racism	Social Media	36764
Systemic Racism	International Response	3759
American Politics	Economy	32366
American Politics	Schooling & Education	56
American Politics	Cancel Culture	1146
American Politics	Justice & Legal System	14195
American Politics	Polarization	16639
American Politics	Culture & Arts	768
American Politics	Social Media	4730
American Politics	International Response	301
Economy	Schooling & Education	120
Economy	Cancel Culture	338
Economy	Justice & Legal System	7753
Economy	Polarization	11359
Economy	Culture & Arts	796
Economy	Social Media	19942
Economy	International Response	680
Schooling & Education	Cancel Culture	9
Schooling & Education	Justice & Legal System	44
Schooling & Education	Polarization	137
Schooling & Education	Culture & Arts	172
Schooling & Education	Social Media	281
Schooling & Education	International Response	2
Cancel Culture	Justice & Legal System	400
Cancel Culture	Polarization	2731
Cancel Culture	Culture & Arts	292
Cancel Culture	Social Media	199
Cancel Culture	International Response	8
Justice & Legal System	Polarization	16336
Justice & Legal System	Culture & Arts	148
Justice & Legal System	Social Media	1005
Justice & Legal System	International Response	121
Polarization	Culture & Arts	673
Polarization	Social Media	3141
Polarization	International Response	1666

Culture & Arts	Social Media	684
Culture & Arts	International Response	10
Social Media	International Response	3429

RQ3 investigates the intermedia agenda setting effects between newspapers and Twitter in terms of the substantive attributes and affective attributes, separately. In answering RQ3, Granger causality tests were performed to identify the agenda setter between the two platforms. Results are exhibited in Table 7. As can be seen in Table 7, reciprocities, unidirectional effects and null effects were all observed. In terms of substantive attributes, first, a reciprocity emerged between the agenda of newspapers and that of Twitter in depicting "killing of Floyd" ($F_{\text{newspaper}} = 6.02$, $p < .001$; $F_{\text{Twitter}} = -.015$, $p < .001$). This result suggested that newspapers and Twitter have affected each other in depicting this substantive attribute. The positive coefficient of newspapers' agenda suggests that the more frequently the newspapers covered this topic, the more frequently the Twitter users would discuss it. However, the negative coefficient of Twitter's agenda suggests that, the more frequently Twitter users discuss on the killing of Floyd in the Twittersphere, the less likely the newspapers would cover it. This causal relationship is inferred and buttressed by the predictive power of the Granger causality, which is useful to reveal precedence (Diebold, 2004; Leamer, 1985).

Moreover, in depicting the 2020 Election, newspapers have exerted a more powerful top-down impact on Twitter discussions ($F_{\text{newspaper}} = 22.08$, $p < .05$). The result suggests that the more saliency the newspapers place on the 2020 election in their coverage of the BLM movement, the more likely the Twitter users discussed this substantive aspect in the

Twittersphere. The newspapers have also exerted a top-down impact in terms of the substantive attributes of police and policing ($F_{\text{newspaper}} = 28.91$, $p < .05$), indicating that the saliency of this substantive attribute placed by the newspapers have led to the saliency of it in the Twitter discussions. Similarly, newspapers' agenda has positively predicted Twitter discussions in terms of the substantive attribute of COVID-19 ($F_{\text{newspaper}} = 4.11$, $p < .06$ [marginal significant]), systemic racism ($F_{\text{newspaper}} = 41.64$, $p < .05$), and cancel culture ($F_{\text{newspaper}} = 15.14$, $p < .01$). However, the newspapers' agenda was found a negative predictor of Twitter discussions in terms of political polarization ($F_{\text{newspaper}} = -45.02$, $p < .05$). This denotes that the more newspapers have emphasized political polarization in their BLM movement-related coverage, the less likely the Twitter users discussed this substantive attribute in their posts about the BLM movement.

In addition to the role the newspapers' agenda has play in predicting Twitter's agenda, the latter has also exerted a bottom-up impact on the agenda-setting of newspapers. As can be seen in Table 7, the more frequently Twitter users discussed on violence ($F_{\text{Twitter}} = .001$, $p < .05$), economy ($F_{\text{Twitter}} = .001$, $p < .05$), culture and arts ($F_{\text{Twitter}} = .021$, $p < .06$ [marginal significant]), and international responses ($F_{\text{Twitter}} = .998$, $p < .05$), the more the newspapers covered these attributes later. When it comes to affective attributes, however, both platforms did not have the ability to influence its counterpart ($F_{\text{newspaper}} = -.003$, $p > .05$; $F_{\text{Twitter}} = -.0003$, $p > .05$).

From these results, one can draw the following conclusions. First, a reciprocity has emerged, which aligned prior research that Twitter has the ability to interact with traditional media rather than being a passive consumer media's agenda (Valenzuela, 2017). Second, although Twitter has some bottom-up impact, newspapers' agenda remained powerful in predicting more substantive attributes for the social media users (Guo et al., 2019). Finally, intermedia agenda setting effects only emerged in depictions of substantive attributes; in terms of emotional attributes, neither traditional media nor social media seem to be able to exert any influence on the other party.

Table 7. Granger causality modeling between newspapers and Twitter in terms of substantive attributes and affective attributes, separately.

	Newspaper → Twitter	Twitter → Newspaper
Substantive attributes		
Killing of Floyd	**6.020*** **	**-.015*** **
The 2020 Election	**22.081***	.0004
Demonstration & protest	36.948	.0002
Police & policing	**28.912***	.001
COVID-19	**4.113†**	.002
Violence	8.958	**.001***
Systemic racism	**41.637***	.0003
American politics	12.247	.001
Economy	5.387	**.001***
Schooling & education	-.401	-.004
Cancel culture	**15.138****	-.001
Justice & legal system	5.995	-.0003
Political polarization	**-45.018***	.001
Culture & arts	-.103	**.021†**
Social media	-31.573	.0003
International response	.927	**.998***
Affective attributes	-.003	-.0003

Note. †$p < .06$ (marginal significance), *$p < .05$, **$p < .01$, ***$p < .001$

RQ4 investigated the intermedia agenda setting effects between newspapers and Twitter in terms of the substantive attributes combined with affective attributes, separately. In answering RQ3, Granger causality tests were conducted to identify the agenda setter between the two platforms. Results are exhibited in Table 8. As Table 8 suggests, in depicting COVID-19 in a specific affective attribute, the newspapers' agenda has the ability to predict the Twitter's agenda ($F_{\text{newspaper}} = .115$, $p = .053$ [marginal significant]). In other words, the more the newspapers depicted COVID-19 with a given affective attribute, the more the Twitter users discussed on the same topic with the same affective attribute. This result is intriguing but also reasonable. As discussed earlier, the substantive attribute of COVID-19 was depicted with a relatively neutral valence in both newspapers and Twitter's agendas.

Table 8. Granger causality modeling between newspapers and Twitter in terms of substantive attributes and affective attributes combined.

	Newspaper → Twitter	Twitter → Newspaper
Substantive attributes combined with affective attributes		
Killing of Floyd	-.028	-.009
The 2020 Election	.058	-.139
Demonstration & protest	.004	.185
Police & policing	-.035	.074
COVID-19	**.115†**	-.012
Violence	.011	-.277
Systemic racism	.042	-.190
American politics	.003	-.099
Economy	-.017	-.001
Schooling & education	.193	-.053

Cancel culture	.057	-.099
Justice & legal system	-.024	.436
Political polarization	-.004	.379
Culture & arts	-.020	.029
Social media	.086	-.093
International response	.050	.004

Note. †p = .053 (marginal significance).

RQ5 asked about the intermedia agenda setting effects between newspapers and Twitter in terms of the bundled substantive attributes. The following steps were taken in addressing RQ5. First, following previous studies (i.e., Guo et al., 2019), descriptive statistics of the edges in the network agendas of both newspapers and Twitter were combined, and the top seven sets of bundled substantive attributes were chosen to be analyzed. Next, Granger causality tests were conducted to identify the agenda setter in terms of these bundled substantive attributes. Results are shown in Table 8. As Table 8 exhibits, several unidirectional intermedia agenda setting effects emerged. Newspapers were found to be powerful in setting Twitter's agenda in terms of the following bundled substantive attributes: Demonstration & Protest—Police & Policing ($F_{\text{newspaper}} = 28.32$, $p < .05$), Police & Policing—Systemic Racism ($F_{\text{newspaper}} = 21.53$, $p < .01$), and the 2020 Election—American Politics ($F_{\text{newspaper}} = 9.49$, $p < .05$). In other words, the more the newspapers bundled the above substantive attributes together in a single coverage, the more the Twitter users mentioned these substantive attributes together in their posts about the BLM movement.

Twitter was also found to set a few bundled substantive attribute agendas for newspapers.

Specifically, the more the Twitter users bundled Police & Policing with Violence ($F_{\text{Twitter}} = .001$, $p < .05$), and Demonstration & Protest with Violence ($F_{\text{Twitter}} = .001$, $p < .05$), the more the newspapers paired these substantive attributes in their coverage of the BLM movement.

Three conclusions can be inferred from the results of the bundled substantive attributes. First, no reciprocal effect emerged at the bundled level. Second, the IAS power of both newspapers and Twitter have shrunk in influencing their counterpart in terms of the bundled substantive attributes. Finally, that being said, newspapers' agenda is still more powerful in influencing Twitter than the other way around.

Table 9. Granger causality modeling between newspapers and Twitter in terms of bundled substantive attributes.

	Newspaper → Twitter	Twitter → Newspaper
Bundled substantive attributes		
Police & Policing—Violence	23.506	**.001***
Killing of Floyd—Police & Policing	.832	.022
Demonstration & Protest—Police & Policing	**28.323***	.000
Demonstration & Protest—Violence	16.840	**.001***
Police & Policing—Systemic Racism	**21.531****	.001
Violence—Systemic Racism	19.327	.000
The 2020 Election—American Politics	**9.492***	.002

Note. *$p < .05$, **$p < .01$.

RQ6 examined the intermedia agenda setting effects between newspapers and Twitter in terms of the bundled substantive attributes, combined with affective attributes. Same analysis was performed to address RQ6. As can be seen in Table 10, no significant effect can be found between both agendas. The null effect implies that when it comes to the most complex agenda setting level, namely, the bundled substantive attributes with specific affective attributes applied, both media platforms have lost the agenda-setting impact on their counterpart.

The elite media may have huge disagreements with the public in terms of *what* topics worth discussing, *how* to make logical and meaningful linkages across different topics, and *what* affective attitudes and stances should be taken to discuss these linked topics. The reasons for these disagreements may be quite inherit, which makes the mutual influence no longer possible. Specific reasons and implications are detailed in the discussion section.

Table 10. Granger causality modeling between newspapers and Twitter in terms of bundled substantive attributes combined with affective attributes.

	Newspaper → Twitter	Twitter → Newspaper
Bundled substantive attributes combined with affective attributes		
Police & Policing—Violence	.031	0.226
Killing of Floyd—Police & Policing	-.010	.080
Demonstration & Protest—Police & Policing	-.006	.104
Demonstration & Protest—Violence	-.037	.325
Police & Policing—Systemic Racism	-.042	-.240
Violence—Systemic Racism	-.014	.022
The 2020 Election—American Politics	.037	.011

In-depth Interviews

Research questions 7 and 9 pertain to the journalists' insights into the impact of Twitter on their work routines and professional norms. Before addressing the research questions, it is important to describe certain demographic characteristics of the seven qualitative participants. In terms of race, six interviewees were white (85.7%), and one was Asian (14.3%). In terms of gender, four were female (57.1%), and three were male (42.9%). Table 11 shows the characteristics of the interview participants.

Table 11. In-depth interview participants

Pseudonym	Gender	State in which the media is located	Description of job title
Interviewee A	Male	California	Reporter
Interviewee B	Male	Illinois	Reporter
Interviewee C	Female	California	Political editor
Interviewee D	Female	California	Sports reporter
Interviewee E	Male	California	Political reporter
Interviewee F	Female	New York	Staff writer
Interviewee G	Female	Massachusetts	Political writer

Before analyzing the participant' personal insights, it also deems beneficial to summarize the frequencies with which these interviewees, as journalists in mainstream newspapers, use Twitter (e.g., Johnson et al., 2018; Lewis & Reese, 2009; Lorenzano, 2018; Parmelee, 2014). According to the result, all of the interviewed journalists have at least one Twitter account. A clear majority of the interviewed journalists (six out of seven) use Twitter in a daily basis, one journalist uses it once to twice a week.

RQ7 inquired about how Twitter affects journalists in terms of their work routines and published works. Throughout the in-depth interview, I found that the interviewed mainstream media journalists mainly endow Twitter with a dual role, namely, (1) a news source hub and (2) a self-branding and promotion platform. Specifically, on the one hand, the interviewees acknowledged that the rich technical features and affordances of Twitter have broadened their scope of sourcing. On the other hand, they were not simply being passive consumers of Twitter, instead, tend to take full advantage of the platform for self-branding and expanding their readerships. In what follows, I shall detail both roles the interviewed journalists have endowed Twitter with.

Twitter as a News Source Hub

According to the interviewees, Twitter is used to gather information or source for storytelling. When discussing about these statements more in-depth, the interviews clearly showed that the manifestation of Twitter's role as a sourcing tool is threefold. First, Twitter makes it easier for journalists to reach out to potential interviewees. Second, contents on Twitter (such as comments) are directly quoted in news reports as a substitute for real interviews. Third, trending topics on Twitter were treated as a tip sheet sparking new story ideas.

In terms of Twitter's role in helping journalists reach out to potential interviewees more easily, interviewee B said that she has used Twitter to reach her target interviewee as "you can easily access [their] emails or [telephone] numbers from their Twitter profiles." When asked to explain in-depth, interviewee B gave the following account:

> "Recently we had [a shooting in Chicago] … a doctoral student, an international student at the University of Chicago shot by allegedly… by a gunman… We needed to reach out to some of his classmates and department staffs who know him when we were trying to put together follow-ups. For that purpose we turned to Twitter because you know, that was perhaps the best way to reach out to a university crowd…Simply search by the name

of the victim and the name of his department and you are good to go" (Personal communication, February 2021).

In addition to approaching people through Twitter, the journalists also see Twitter as helpful in sourcing because of the opportunity to incorporate Twitter comments in their own stories. All of the interviewed journalists said that they themselves have, or have seen others, quoted Twitter comments in their stories. For example, interviewee D said:

> "I almost always have a Twitter tab open as I work, scrolling through to stay updated on the day's major stories, and the internet's reactions…Not until this year did I include public comments on Twitter and Instagram as valid sources within stories." (Personal communication, January 2021)

When asked to elaborate in-depth, interviewee D gave the instance that in writing a story about Jill Biden's calling on people to wear masks while walking dogs, she and her colleagues have directly quoted Twitter comments in their stories as an alternative of real interview. Including public comments on Twitter is particularly effective amid the current pandemic, when social distancing is still implemented and, according to interviewee D, when it is especially "hard to interview as many people as we could in ordinary times."

Moreover, tweets from ordinary users at large were also considered to serve as a "tip sheet" inspiring new story ideas. A few interviewed journalists have elaborated on how Twitter helped them to effectively find some hard-to-reach sources. Interviewee A said that he sees Twitter as an "inexhaustible source of topics." Interviewee C said that she sees Twitter as a "tip sheet" sparking new ideas. According to interviewee C, "Twitter can make reporting itself easier and more accessible, you know. Like, I can trace an online trend, like Bernie Sander's viral mittens, back to its source, or I can survey real-time reactions to world events effortlessly."

Besides, the functionalities of Twitter such as hashtags have also been used for analyzing and understanding trending topics as well as public sentiments. For instance, interviewee F stated,

> "…understanding public opinions has long been part of journalists' work, and the tools for doing so have always been imperfect. Any individual journalist can only interview so many people directly. Journalists all must have other methods for generalizing about the feelings of a large mass of people. Twitter is one such method. It is good because it is large, fast, and has tools, you know, like hashtags, that allow for analysis." (Personal communication, February 2021).

Twitter as a Self-Promotion Platform

The influence between Twitter and journalists is reciprocal rather than unidirectional. In addition to using Twitter as an effective sourcing tool, all interviewed journalists unanimously said that Twitter is an ideal platform for them to build their personal brands and promote their own works. This effort has two motivations. First, as some journalists reported, they take full advantage of Twitter to brand themselves, so as to "elevate the impact" of their most updated stories. This is particularly valued because when a journalist has "developed a fairly high profile," he or she would cultivate "a group of regular readerships" that would "stay tuned to all his pieces in [the] future." As interviewee G has reported,

> "For the most part, it seems to me that the expectation is to tweet out each of your stories, or if you're a breaking news reporter, perhaps the ones you're most proud of, as they're published. It's a form of updating your professional social circle as to where you are and what you're up to." (Personal communication, February 2021).

The second motivation pertains to organizational expectations. In other words, using Twitter is also expected and encouraged by the media outlets where the journalists are serving for. According to the interviewed journalists, all of their organizations encouraged them to "use whatever social media" they have. Some reported that the organizational had a "big push" to make sure all their newsroom staffs have an official Twitter account, and no one left behind. The very purpose is to "boost social media visibility," "communicate with the wider public," and "cultivate readerships." For instance, interviewee B specified,

> "Twitter has allowed individual journalists to acquire a direct platform for communicating with the wider public. Rather than being simply a name on an article in a larger newspaper, journalists can become well-known in their own right. This has made journalists more likely to be outspoken in sharing their own views online. It has also become much more common, and actually encouraged by many news outlets, for journalists…to promote their own work and their own brands on Twitter.". (Personal communication, February 2021).

In a nutshell, mainstream media practitioners, on the one hand, take full advantage of the functionalities of Twitter to maximize their work efficiency, and on the other hand, use Twitter as an effective platform for branding and self-promotion. Taken together, apart from (1) reaching out to potential interviewees through Twitter, (2) incorporating Twitter comments into stories as an alternative to real-life interviews, and (3) being sparked new ideas through browsing Twitter feeds, the professional work of mainstream media practitioners still shows a considerable extent of independence. In other words, journalists are more likely to use Twitter to *aid* reporting and to *promote* reporting, while their basic work structure, elements, and demands as traditional media practitioners have remained unchanged. This finding echoes a previous study, which suggested that compared to BuzzFeed's own journalists, journalists in traditional organizations were less likely to adopt a rather strong orientation toward the audience, as the latter is reluctant toward "compromising autonomy" (Tandoc Jr & Foo, 2018, p. 53).

These findings well explain the results of the big data analysis. Specifically, the effects of intermedia agenda-setting at the substantive attribute level, albeit reciprocal, denoted that newspapers still had greater influence on Twitter. This is most likely due to the journalists' self-promotion on Twitter. Although the vitality of newspapers is constantly being weakened with the rapid improvement of media technology and the drastic revamp of the media landscape, media practitioners' efforts in combining the two, whether out of organizational expectations or personal benefits, have boosted and expanded the audiences for the traditional media such as newspapers. Due to the journalists' continuous use of Twitter to promote their own works, those mainstream media reports can either directly or randomly reach the scattered social media users, who may not be direct subscribers or readers of those newspapers. As a result, even if these scattered social media users are not audiences of mainstream media at all, it is difficult for them to completely avoid the penetration of mainstream media agendas on social media. This also explains why newspapers are still maintaining their dominant ability in intermedia agenda setting in the age of social media, especially in terms of substantive attribute agendas. When it comes to Twitter's bottom-up impact at the substantive attribute level, the reason could be related to the journalists' use of Twitter as an effective sourcing tool in the aforementioned three dimensions. The incorporated Twitter comments, the summarized public opinions, and the story ideas sparked by the Twitter feeds might be the explications of Twitter's bottom-up influence found in the previous big data analysis.

Twitter as a Prism of Distorted Views

RQ8 further asked about the ways in which the journalists assess the impact of the public sentiment on Twitter on their journalistic work as well as the professional norms of journalism. The interviews clearly showed that all journalists exhibited a considerable extent of vigilance against the public sentiments shown on Twitter. In fact, the majority of journalists I spoke with expressed concerns with respect to inferring public sentiments from their own feeds, which "could be extremely narrow." Four journalists reported that they often use Twitter to understand "trending topics" and get new story ideas at the episodic level, but meanwhile, they were wary of the fairness of the public sentiments and attitudes reflected in Twitter. For instance, interviewee

A provided the following insights, “I know what people are paying attention to over a period of time, but Twitter doesn’t necessarily reflect more general attitudes fairly.”

The concern about the fairness and comprehensiveness of Twitter in reflecting public sentiment was echoed by many similar responses. For instance, Interviewee E said, “…like any tool, it can provide a distorted view of trends and public sentiments if used in certain ways.” Interviewee C and E reported that although they have been using Twitter for sourcing, they haven’t incorporated much of the public sentiments on Twitter in their own reports because they believe that Twitter cannot reflect a full picture of public sentiments. Interviewee E said,

> “It feels to me that journalists increasingly risk viewing Twitter as reflective of the world at large, when it is in fact far from it…The more online journalists become, the more we shift our viewpoints toward those similar to us, with resources and access to Internet culture.” (Personal communication, February 2021).

Juxtaposing RQ7 and RQ8, it can be inferred that the journalists were overwhelmingly optimistic about the value and function of Twitter in sourcing and self-promotion, but they are quite wary of the fairness of Twitter in reflecting public sentiments and viewpoints. These interview results also revealed the internal mechanism of the big data analysis results. Specifically, the journalists were more open to turn to Twitter in terms of the substantive aspects of an issue, such as using the affordance indicator of hashtag to make sense of what has been discussed most heatedly and the topics on top of the public concerns. Although the trending topics and sources on Twitter have functioned as tip sheets that sparked the journalists’ story ideas and provided them with rich story materials, the journalists were reluctant to incorporating the public sentiments and viewpoints reflected in those Twitter discussions in their own stories, as they appeared to be cognizant of the existence of the spiral of silence and the effects of echo chambers, as well as the resulting distorted picture of public sentiments and attitudes. This finding explains why, as shown in the big data analysis, asymmetrically reciprocal intermedia agenda setting effects emerged at the level of substantive attribute agendas, while shrank significantly when it comes to the level of affective attribute agendas.

CHAPTER FIVE

DISCUSSION

In the current media landscape, the traditional media, and print publications in particular, has struggled to survive due to the significantly declining subscriptions, the rapidly shrinking market share, and the growing challenge posed by emerging media. Statistics show that newspaper circulation in the U.S. has fallen, in the year of 2018, to its lowest level since 1940, and particularly, newspaper revenues in the U.S. have witnessed the most dramatic decline from 2008 through 2018 (Pew Research Center, 2020a). Comparably, social media has emerged and grown significantly during the same period (Pew Research Center, 2018; Suciu, 2019). A report documented that in 2018, social media first outpaced newspapers in the U.S. as a news source (Pew Research Center, 2018). This trend has been intensifying (Suciu, 2019). Hence, it is safe to say that the ubiquity of social media has been one of the main reasons of newspapers' decline (Kushin, 2010).

Against this background, this dissertation strives to understand the interplay between mainstream newspapers and Twitter, one of the most representative social media platforms through which people consume news information frequently, in terms of the attribute agendas revolving around a major issue, the BLM movement. To be specific, the purpose of this dissertation was threefold. First, this dissertation strives to delineate the ways in which the mainstream newspapers of the U.S. and Twitter set network agenda-setting models for the BLM movement in 2020. Second, this dissertation seeks to understand whether nor not there is intermedia agenda setting effect between the newspapers and Twitter in various dimensions. Third, this dissertation aims to examine how the mainstream media practitioners understand and evaluate Twitter's impact on their work routines and professional norms of journalism. The following aspects of the findings merit further discussions.

First, through network analysis, this dissertation revealed the ways in which the newspapers and Twitter set network agendas for the BLM movement. In terms of substantive attribute agenda, which is reflected in the nodes in both network visualizations, newspapers have featured the 13 attributes with relatively equal amount of attention, compared to Twitter. Specifically, the size of nodes in newspapers' network did not show as big differences as that of Twitter. This phenomenon indicates that newspapers, as a type of traditional media, tended to devote similar attention to the various attributes of an issue. This might be due to the principle of balance in journalistic professionalism by which the journalists are committed to abiding (Lewandowsky et al., 2012). However, public opinions on social media appeared to be far more biased towards what attributes are being discussed more frequently.

In terms of the affective attributes, apparently, all the substantive attributes in the newspapers' agenda are depicted with the pro-movement valence, reflected in the color (i.e., blue) of the nodes. This indicates that no matter what aspect of the BLM movement the newspapers have reported on, they used a supportive valence. However, there are also nuances in the largely supportive valence used by the newspapers. When covering the attributes of "systemic racism," "killing of Floyd," "polarization" and "violence," the newspaper agenda used more strongly supportive tone. In depicting “culture & arts,” “COVID-19” and “international responses,” the newspapers appeared to be neutral-leaning. This is understandable as these three substantive attributes are not as political, nor do they pertain to the core concerns of the issue at hand. When it comes to Twitter, oppositely, all the attributes were discussed in a condemning tone but also of varying extents. Twitter users appeared to have stronger sentiment against the movement when discussing about “polarization,” “justice and legal system,” “cancel culture,” and “the 2020 election.” A closer read of the tweets showed that a large amount of Twitter users condemned that the BLM movement can only intensify the ideological polarization of the American society. Many tweets also expressed concerns and condemnations of the rioting action of the protests, which they believe are illegal. Furthermore, users also indicated that the cancel culture, such as the removal of Confederate monuments and memorials, is a type of cultural revolution and so-called “racial reckoning” that has gone too far. This sentiment is reflected in a tweet “*Other minorities also exist. The decentralization of justice through social media enables camaraderie. But much like cancel culture, I feel like BLM may be wrong in some places.*” Comparatively, Twitter users did not use a strong valence when discussing about “social media,” “COVID-19,” and “schooling & education.”

One reason of Twitter’s overall condemning valence on the BLM-related discussion could relate to the existence of the spiral of silence. The spiral of silence states that fearing isolations, an individual would keep silent rather than voicing opinions in a group if he or she found that most of other group members hold different opinions (Noelle-Neumann, 1974).

Speaking of the discussions on the BLM movement, some social media users, even being supportive of the movement, could become silent once they find that the criticisms are too strong (Gearhart & Zhang, 2015).

In terms of the bundled substantive attributes, “police & policing” and “violence” are the most frequently co-occurred substantive attributes in the newspapers’ agenda. This means that when covering the BLM movement, the mainstream U.S. newspapers tended to mention both elements at the same time. The second most frequently co-occurred substantive attributes in the newspapers’ agenda are “Killing of Floyd” and “police & policing.” Taken together, one can easily infer that the mainstream newspapers attached greater significance to how the police brutality during the movements. When it comes to Twitter’s agenda, “police & policing” and “violence” are also the most frequently co-occurred substantive attributes in the newspapers’ agenda. However, interestingly, the second most frequently co-occurred substantive attributes in Twitter’s agenda are “demonstration & protest” and “violence.” This indicate that unlike the newspapers, Twitter users attach similar amount of attention to the brutality of both the police and the demonstrators.

In sum, the NAS models of the newspapers and Twitter are different in several ways. They are different in terms of *what* substantive aspects to be discussed, *how* to use affective valences when discussing about these aspects, and *what* aspects to be covered simultaneously. Newspapers tended to discuss more about the police brutality, systemic racism and killing of Floyd, using a supportive tone to the BLM demonstrators, while the Twitter users tended to discuss about the same aspects but using a condemning tone. Moreover, newspapers only linked "police" with "violence," while Twitter users not only linked both attributes but also attached similar significance to the association between "protest" and "violence."

In addition to looking into the network agenda-setting between both platforms, this dissertation examined how the agenda of both media interact with each other at multiple levels, from the perspective of intermedia agenda setting. In terms of the substantive attribute, findings show that multiple intermedia agenda setting effects have emerged. There is a reciprocal effect between the newspapers and Twitter in terms of the substantive attribute of "killing of Floyd," where the newspapers' agenda positively predicted Twitter while Twitter negatively predicted newspapers. In other words, the more newspapers covered the death of Floyd, the more Twitter users discussed about the same topic, while the more Twitter users discussed about the killing of Floyd, the less likely the newspapers covered about it. Therefore, although the IAS effect of this topic showed as reciprocal, newspapers, in fact, have exhibited positive and stronger agenda-setting impact on Twitter. This observation echoes previous argument that traditional media, albeit declining in agenda-setting influence in this digital age, still has irreplaceable power to set agendas for the public discussions in social media spheres, especially for political and cultural topics, such as social movement, election and policy making (e.g., Groshek & Groshek, 2013; Harder et al., 2017; van den Heijkant et al., 2019). As analyzed earlier, this could be due to the fact the elites usually possess numerous accesses to various resources that ordinary people do not have, such as government officials, institutions and other entities, hence, traditional media can tell a story with abundant resources and details. Social media users only discuss about the topic using what they have learned from the coverage of traditional media. This argument is further buttressed and bolstered by the finding that newspapers have also influenced Twitter’s agenda unidirectionally for “the 2020 Election,” “police & policing,” “COVID-19,” “systemic racism,” and “cancel culture,” which are all the aspects and dimensions of the movement that have largely been politicized (e.g., Hart, Chinn & Soroka, 2020). While Twitter unidirectionally predicted newspapers’ agenda for “violence,” “economy,” “social media,” and “international responses.”

Taken together, the findings indicate that (1) newspapers possess an overall stronger impact on social media in terms of substantive attribute agendas, particularly for political and cultural topics, (2) that said, social media’s agenda is also able to set substantive attribute agendas for newspapers, but the influence is limited as shown in the amount of topics, and the topics Twitter influenced newspapers are less political. This finding is largely consistent with previous studies (e.g., Groshek & Groshek, 2013; Harder et al., 2017; Kim et al., 2016; van den Heijkant et al., 2019).

However, one thing intriguing is that newspapers have negatively predicted Twitter’s agenda in terms of “political polarization.” This means that the more the newspapers cover about political polarization within the issue of the BLM movement, the less likely the Twitter users would discuss about it. This finding is interesting while unsurprising. Indeed, in recent years, the American people, especially conservatives, have shown continued decline in trust in elite media (Pew Research Center, 2019; Pew Research Center, 2020b). On the one hand, it may be because the former president's slander on these media has successfully affected and shaped people's attitudes; on the other hand, it may also be due to the fact that audiences have been increasingly dissatisfied with the biases exhibited in these media. Recent surveys have shown that the increasingly intensified partisan dynamics have overshadowed other factors in American people's evaluations of the news media, where Republicans in particular have consistently expressed great skepticism of the news media and their motives (e.g., Pew Research Center, 2019). Therefore, seeing the mainstream media themselves as renderers and exacerbators of political polarization, the social media users would be more likely to be immune to the coverage of these media on the attribute of political polarization.

When it comes to affective attribute agenda, null effect was observed. This finding indicates that neither newspapers nor Twitter affected each other's affective attributes when discussing about the BLM movement. The mutually independency aligned with previous finding (e.g., Su et al., 2020). The reason is manifold. In terms of newspapers, there are typically various decisive factors that serve as the antecedents of traditional media's agenda-setting, including their political stances, ideological camps, sponsorships, and sources of funds. Therefore, traditional media's agenda-building and -setting were not prone to be adjusted or affected simply by discussions in social media.

This argument is further bolstered by my in-depth interview results. As my interviews have shown, most of the journalists, albeit being optimistic about Twitter's role in assisting reporting and sourcing, were largely skeptical toward the public sentiments in Twitter. Many reported concerns about the distorted views of public opinions and sentiment reflected by Twitter. The interview results well revealed the mechanism as to why newspapers and Twitter can have either reciprocal or unidirectional impact on each other but did not show any mutual impact at the affective attribute level. In a nutshell, (1) the underlying reason of Twitter's impact on newspapers in terms of substantive attribute agenda pertains to journalists' frequent use of Twitter as a tool to make sense of trendy topics and for sourcing, this way, journalists' have incorporated the substantive attribute in Twittersphere into their own stories. (2) The reason of newspapers' impact on Twitter in terms of substantive attribute agenda pertains to journalists' self-branding and promotion on Twitter; to be specific, promoting stories on Twitter can provide more opportunities for the digital citizens and Twitter users to be exposed to newspaper coverage. Of course, the traditional media's inherent and persistent agenda-setting power, even without the help of social media promotion, is also playing a role to influence the social media discussions. (3) The null effect between both media outlets in terms of affective attribute agenda pertains to the fact that both journalists and Twitter users are skeptical toward the fairness and unbiasedness of its counterpart. In other words, although journalists oftentimes adopt trendy topics in Twitter as their story ideas, they barely follow the tones and valences Twitter users have used in their discussions, and vice versa.

The above investigations of the IAS effects between both platforms at the substantive and affective attribute levels separately are mainly about the traditional second-level intermedia agenda-setting effects. The NAS model theorizes that media has the ability to bundle different elements and transfer the bundled agenda to the public (Guo & McCombs, 2011; Vu et al., 2014). Therefore, I took a step further and examined the interplay between both platforms in terms of the combined substantive and affective attributes. The results show that the intermedia agenda-setting effects for both newspapers and Twitter have shrunk significantly. No significance has emerged in addition to newspaper's marginal impact on Twitter on the attribute of "COVID-19." The finding is understandable as throughout the entire BLM movement, the attribute of the pandemic involves relatively little ideological divergence and polarization. In other words, it might be easier for both the elite mainstream media and the ordinary social media users to reach a consensus on the fact that excessive streets activities are not conducive to the epidemic prevention and control. This is particularly true comparing to other attributes that are more likely to cause value divisions and disagreements, such as policing, racism, domestic politics, and the judicial system.

According to the NAS research, the media gestalt is not confined to the bundled substantive and affective attributes, it also denotes the bundled substantive attributes (e.g., Guo et al., 2015; Wu & Guo, 2020) and the combination of affective attributes and the bundled substantive attributes (e.g., Guo et al., 2019; Guo & Vargo, 2015). Therefore, I also examined the intermedia agenda setting effect between newspapers and Twitter in terms of (1) the bundled substantive attribute agenda and (2) the combination of the bundled substantive attribute and the affective agenda. In doing so, first, I selected seven most frequently co-occurred substantive attributes as directed by prior research on network IAS (e.g., Guo et al., 2019). The results are largely consistent with the IAS pattern of unbundled substantive attributes between both platforms. In specific, newspapers have influenced Twitter on three bundled substantive attributes, namely, “Demonstration & Protest—Police & Policing,” “Police & Policing—Systemic Racism,” and “The 2020 Election—American Politics.” Twitter has affected the newspapers on two bundled substantive attributes, that is, “Police & Policing—Violence” and “Demonstration & Protest—Violence.” All the effects are positive. According to these results, one can infer that newspapers are more powerful and influential in bundling agendas for political, cultural and institutional aspects of the issue, such as policing, racism and the election, while Twitter is more powerful in bundling agendas for incidental aspects of the issue, such as the violence in both the police and the protesters. This finding not only echoed previous statement that legacy media are capable to shape the agenda of the publics, especially for political and cultural topics, such as social movement, election and policy making (e.g., Groshek & Groshek, 2013; Harder et al., 2017; van den Heijkant et al., 2019), but also well aligned with the argument of a prior research that Twitter is more likely to affect newspapers’ agenda in terms of breaking news, while “newspapers are more likely to lead Twitter’s agenda in terms of ongoing discussions” (Su & Borah, 2019, p. 236).

Lastly, when the bundled substantive attributes were combined with specific affective attributes, no significant intermedia agenda-setting effect has been observed (see Table 10). Findings suggest that the limitation of the agenda-setting hypothesis could emerge when we move from issues and attributes toward more sophisticated ideas, such as the various dimensions of the attributes and their combinations.

The in-depth interviews have well explained the findings about the network IAS effects between both platforms. First, a plethora of reciprocities and one-way IAS effects have emerged between newspapers and Twitter at the levels of substantive attributes and the bundled substantive attributes, which might be due to the facts that journalists have not only been using Twitter as a tip sheet sparking new story ideas and a sourcing tool, but also been using Twitter to promote themselves and their published works. Specifically, Twitter affected newspapers coverage because sources and trending topics from the Twittersphere have flowed in journalists' stories, while newspapers also influenced Twitter because journalists oftentimes promote their stories on these platforms, allowing social media users to be exposed to traditional media coverage from time to time. Second, the IAS effects of both platforms have significant shrunk when it comes to the affective attribute agenda and the combination of the affective attribute and the bundled substantive attributes, which might be due to the facts that journalists had concerns about the fairness and completeness of the public sentiments reflected in the Twittersphere and the social media users are also skeptical toward the unbiasedness of the mainstream media (Pew Research Center, 2019; Pew Research Center, 2020b).

Implications

The theoretical contribution and practical implication of this dissertation is manifold. One of the primary takeaways of the analyses on the NAS models of the newspapers and Twitter is that both platforms utilized distinctive valences to depict the substantive attributes. Although both the newspapers and Twitter have paid relatively more attention to systemic racism, violence, police and policing, and demonstration and protest, the newspapers have reported on these substantive dimensions using a supportive tone, while Twitter users used a condemning tone. This finding directly reflects the contradictory emotional tendencies and ideological stances held by the mainstream, elite media and the ordinary Twitter users in the United States when talking about a same issue. The public's immunity and resistance to mainstream media's ideology may have been shaped by a series of far-reaching political and societal factors, while mainstream media practitioners, rather than being dismissive of the public sentiments reflected on Twitter, do not trust nor feel assured about the functionality of Twitter in reflecting an unbiased and undistorted picture of public sentiment. Therefore, one of the effective ways to bridge the gap between mainstream media and social media users' affective attributes is that journalists can consider using multiple social media platforms, rather than Twitter alone, to make sense of what the publics are thinking about an issue. Previous scholars have already argued that different social media platforms can reflect distinctively different patterns of public opinions on same issues (e.g., Choi, Matni & Shah, 2016; Flores, 2017; Lukito, 2020).

When it comes to the intermedia agenda-setting effects between the two platforms, findings first suggested that newspapers still have a stronger impact on Twitter at both the substantive and affective attribute agenda levels. The finding is consistent with a large amount of prior research that showed the same agenda flow (e.g., Ceron et al., 2016; Groshek and Groshek, 2013; Harder et al., 2017; Heijkant et al., 2019; Kim et al., 2016; Vargo et al., 2018; Yang & Kent, 2014). Despite the rapid development of social media and the increase of its agenda-setting influence, newspapers still possess a stronger capability to transfer its agenda to the public. Moreover, as prior studies have consistently argued that newspapers' agenda-setting power can become particularly stronger on political and cultural issues, the current dissertation provided more evidence to support this argument.

Furthermore, although Twitter did not exert a stronger IAS impact on the newspapers, it still influenced the latter on the depictions of some substantive and affective aspects of the issue. This finding well aligned with a growing body of literature that revealed a complex, multidirectional interaction, rather than unidirectional impact, between traditional and social media in the digital age. Mainstream media are benefited from its incomparable access to resources, institutional supports, and financial strengths, hence, it still set agenda for the public. Even though the digital citizens have become more active and outspoken compared to the audience in the non-digital age, they are still largely passive consumers of media content while rarely become producers of first-hand information. Social media users' influences are reflected more on their abilities to "break free from and influence traditional media gatekeeping" (Conway-Silva et al., 2018, p. 469), contribute to "an expansion of the elite" (Rogstad, 2016, p. 142), become "competing agenda-setting forces" (Luo, 2014, p, 1289), and sometimes influence the traditional media in terms of breaking news, thanks to its incomparable timeliness (Su & Borah, 2019).

Last but not least, according to the in-depth interviews, the mainstream media practitioners' attitude toward Twitter is characterized with openness but also reservations. Their openness is manifested by their active usage of Twitter to promote their own stories, self-branding, using trending topics on Twitter as a source of ideas, and openly incorporating tweets as a part of their stories. Meanwhile, they still consistently and firmly hold that Twitter only presents very biased opinions and distorted sentiments and views, which allow them to only interact with Twitter at the issue or substantive attribute levels, while maintaining independence at affective levels.

This dissertation has multiple noteworthy contributions to the agenda-setting research. First, it is the first known attempt to combine big data analysis with qualitative in-depth interviews. The grip of this attempt is obvious. Previous studies only provide a pattern as to *who leads whom*, while this dissertation further revealed the underlying reasons as to *why such pattern emerged*. Specifically, this dissertation not only exhibited a nuanced IAS flow at substantive attribute, affective attribute, and bundled level, but also provided the journalists' experiences and viewpoints explicating these agenda flows.

Second, this dissertation heeds the call to examine "the level of redundancy necessary to create" media's IAS effects among the publics" (McCombs, 2014, p. 793) through inspecting the IAS interplay at five nuanced agenda-setting levels: substantive attribute agenda, affective attribute agenda, combined substantive and affective agenda, bundled substantive attribute agenda, and combined affective attribute with the bundled substantive attribute agenda. In doing so, this dissertation helps us gain a better and more in-depth understanding of both media's impact at various dimensions and aspects of issues.

Furthermore, in terms of the coding and analytical techniques for affective attribute agenda, the utilization of gradient color coding with a 5-point Likert scale has advanced the previous dummy-coding strategy, making the concentration of the affections and valences more concrete and detailed rather than treating it with an either-or criterion. Indeed, newspaper coverage and social media posts are not all in an intense tone, many are characterized with mildly supportive or moderately condemning valences, hence, the application of this gradient color-coding strategy can reflect the affective attribute agenda more accurately. Last but not least, this dissertation analyzed over one million tweets and thousands of newspaper articles. Pundits and scholars have highlighted that a large sample size "allows a more precise estimate of the treatment effect and it usually is easier to assess the representativeness of the sample and to generalize the results" (Biau, Kernéis & Porcher2008, p. 2287).

Practically, given the overall condemning attitudes toward the BLM movement on Twitter and its worrisome antecedents, media scholars and practitioners should attach more significance to the digital media literacy among social media users. Plenty of information fabricated for certain political motives can easily mislead and manipulate the online public opinion. Moreover, lack of fact-checker and gatekeepers on social media has also made digital media literacy education more warranted than ever before (Hameleers, Powell, Van Der Meer, & Bos, 2020).

Limitations and Conclusion

As all studies do, this dissertation has several limitations. Many agenda-setting studies have been suffering from the utilization of purposive sampling, which potentially threats the external validity of the results (Kushin, 2010). This dissertation, albeit using a relatively large sample size compared to previous agenda-setting research, is still limited in that it only selected seven newspapers as representatives. Although the determination of these outlets has robust justifications (e.g., Boyle, 2001; Conway et al., 2015; Golan, 2006; Feeley & Vincent III, 2007; Lee et al., 2005; McCombs, 2005; Towner & Muñoz, 2020; Vliegenthart & Walgrave, 2008), and the sampling has considered both the circulation and ideological spectrum, inferences drawn from this dissertation can hardly be generalized to other types of traditional media, such as broadcast and cable news. Future studies could benefit from investigating other forms and types of mainstream media to improve the causal inference and the external validity of this dissertation. Moreover, the selected newspapers are mainly neutral or liberal in terms of political ideology, analyzing partisan media would be a valuable addition. To overcome the limitation of purposive sampling, future scholars can also consider using some big dataset, such as GDELT's Global Knowledge Graph (GKG) dataset (see Guo & Vargo, 2018 and Leetaru, 2015), which "gathers stories from all national and international news from Google News and allows researchers to computationally analyze news content of varying types" (Guo & Vargo, 2018, p. 187). The same sampling issue is true for the social media sample. Although this dissertation examined a large size of social media sample, it is confined to Twitter. Future scholars could benefit from including other types of social media such as Facebook. Considering the structural differences between Twitter and Facebook, the inclusion and analysis of Facebook data can expectedly provide a different picture of public sentiments and opinions. For instance, many discussions on Facebook are posted in small groups based on shared interests, which is different compared to the openness of tweets, the influence of spiral of silence could be eliminated in these Facebook discussion groups.

Additionally, one of the purposes of this dissertation was to use in-depth interviews to make sense of the IAS effects reflected by time-series analysis, however, I only listened to the insights of newspaper journalists into Twitter's impact, while I did not interview Twitter users to gain an understanding of their opinions on the influence of mainstream media. Admittedly, the large population of social media users may make it extremely difficult to conduct in-depth interview with targeted and representative participants, it does not mean that the opinions of social media users are not worthy of attention. Future scholars might consider using surveys or other strategies to obtain social media users' insights.

Last but not least, although the inclusion of the in-depth interview has fundamental contribution to the intermedia agenda-setting research in the digital society where the relationships among various media outlets have become very complex, the sample size for the interview is limited. Future scholars should consider conducting more interviews with frontline journalism practitioners, such as editors, program anchors, and writers and journalists in various beats, to obtain a more representative and comprehensive understanding of their concerns and viewpoints of social media.

With the rise of the Internet in the 1990s and the emergence of social media platforms at the very beginning of the 21st century, scholars have started enquiring whether the agenda-setting theory is still valid and have been investigating the ways in which this traditional theory could adapt in the digital age (Kushin, 2010; Takeshita, 2005). The discussions, inquiries and thoughts have given birth to the second and third levels of agenda-setting and intermedia agenda setting theory, seeking to delineating the agenda-setting effect at nuanced levels.

This dissertation is anchored by a perspective of network intermedia agenda-setting (Vargo et al., 2018), exploring the ways in which the U.S. mainstream newspapers and Twitter set network agendas for the 2020 BLM movement and the ways in which both agendas interact with each other. Findings show that newspapers and Twitter both put saliencies to the substantive attributes such as police and policing, violence, systemic racism, and demonstrations. However, newspapers depicted these attributes using an overall supportive tone while Twitter users used a largely condemning tone. Furthermore, newspapers usually cover police and violence simultaneously, while Twitter users not only mentioned both attributes at the same time but also frequently talked about demonstration and violence simultaneously. Moreover, both unidirectional and reciprocal effects have emerged between the newspapers and Twitter for substantive attribute alone, while newspapers showed an overall stronger power than Twitter. No effect has been observed for affective attributes. When it comes to the combination of each substantive attribute and specific affective attributes, the IAS effects have shrunk significantly: only one unidirectional while marginally significant effect of newspapers on Twitter was observed for the topic of COVID-19. In terms of the bundled substantive attribute agendas, both newspapers and Twitter showed more impacts on its counterpart, but still, the newspapers were more powerful than vice versa. Lastly, null effect emerged when it comes to the combination of bundled substantive attributes and affective attributes.

In closing, this dissertation was motivated by an acknowledgment that there was sufficient space to further improve our understanding as to who leads whom in this complex and sophisticated media environment, where the communication technologies have been updating and developing drastically. To this end, my expectation is that this dissertation was beneficial and conducive to gaining both a greater and a nuanced understanding of the relationship between newspapers and Twitter, two important outlets representing legacy and emerging media and competing for “the paramount form of power,” namely, the “network-making power” (Castells, 2013, p. 47).

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APPENDIX A: SUPERVISED MACHINE-LEARNING PYTHON SCRIPT

Section 1. Support Vector Machine (SVM) Algorithm Preparation

```
# In[1]:
import numpy as np
import pandas as pd
import csv
import glob
import os
import news_extract as ne
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
get_ipython().run_line_magic('matplotlib', 'inline')
```

Section 1.1. Preparation – Defining Parse and SVM Functions

```
# In[24]:
from nltk.tokenize import word_tokenize
from nltk import pos_tag
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.preprocessing import LabelEncoder
from collections import defaultdict
from nltk.corpus import wordnet as wn
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn import model_selection, naive_bayes, svm
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_recall_fscore_support
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from nltk.tokenize import TweetTokenizer
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, accuracy_score, f1_score
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix, roc_auc_score, recall_score, precision_score
```

```
# In[27]:
def parse_text(Corpus,twitter_stopwords,text_name='text'):
    '''Tokenize twitter/news texts and remove stop words
    Write the list of parsed words in the new column "text_final"'''
    # Step - a : Remove blank rows if any.
    #Corpus['text']=Corpus['text'].dropna(inplace=True)
    # Step - b : Change all the text to lower case. This is required as python interprets 'dog' and
'DOG' differently
    Corpus[text_name] = [str(entry).lower() for entry in Corpus[text_name]]
    # Step - c : Tokenization : In this each entry in the corpus will be broken into set of words
    Corpus[text_name]= [word_tokenize(entry) for entry in Corpus[text_name]]
    # Step - d : Remove Stop words, Non-Numeric and perfom Word Stemming/Lemmenting.
    # WordNetLemmatizer requires Pos tags to understand if the word is noun or verb or
adjective etc. By default it is set to Noun
    tag_map = defaultdict(lambda : wn.NOUN)
    tag_map['J'] = wn.ADJ
    tag_map['V'] = wn.VERB
    tag_map['R'] = wn.ADV
    for index,entry in enumerate(Corpus[text_name]):
        # Declaring Empty List to store the words that follow the rules for this step
        Final_words = []
        # Initializing WordNetLemmatizer()
        word_Lemmatized = WordNetLemmatizer()
        # pos_tag function below will provide the 'tag' i.e if the word is Noun(N) or Verb(V) or
something else.
        for word, tag in pos_tag(entry):
            # Below condition is to check for Stop words and consider only alphabets
            if word not in stopwords.words('english') and word.isalpha() and
word.encode('UTF-8').isalpha():
                if word not in twitter_stopwords:
                    word_Final = word_Lemmatized.lemmatize(word,tag_map[tag[0]])
                    Final_words.append(word_Final)
        # The final processed set of words for each iteration will be stored in 'text_final'
        Corpus.loc[index,'text_final'] = str(Final_words)
    return Corpus

# In[28]:
def svm_train(Corpus,term_list,frame,predict):
    '''SVM Training
    Corpus: Manually coded parsed texts
    term_list the list of coded terms
```

```
    frame: Parsed texts to be coded. When predict==False, set it to 0
    predict: whether or not doing prediction'''
    conf_mat={}
    for term in term_list:
        #Train_X, Test_X, Train_Y, Test_Y =
model_selection.train_test_split(Corpus['text_final'],Corpus['Sovereignty
claim'],test_size=0.3,random_state=1)
        Train_X, Test_X, Train_Y, Test_Y =
model_selection.train_test_split(Corpus['text_final'],Corpus[term],test_size=0.3,random_state=1
)

        Encoder = LabelEncoder()
        #Train_Y = Encoder.fit_transform(Train_Y.astype(str))
        #Test_Y = Encoder.fit_transform(Test_Y.astype(str))

        Tfidf_vect = TfidfVectorizer(max_features=5000)
        Tfidf_vect.fit(Corpus['text_final'])
        Train_X_Tfidf = Tfidf_vect.transform(Train_X)
        Test_X_Tfidf = Tfidf_vect.transform(Test_X)

        # Classifier - Algorithm - SVM
        # fit the training dataset on the classifier
        SVM = svm.SVC(C=1, kernel='linear', degree=3, gamma='auto')

        SVM.fit(Train_X_Tfidf,Train_Y)
        # predict the labels on validation dataset
        predictions_SVM = SVM.predict(Test_X_Tfidf)

        conf_mat[term] = confusion_matrix(Test_Y, predictions_SVM)
        # Use accuracy_score function to get the accuracy
        print(term)
        #print("SVM Accuracy Score -> ",accuracy_score(predictions_SVM, Test_Y)*100)
        print(precision_recall_fscore_support(predictions_SVM, Test_Y, average='weighted'))

        if predict==True:
            All_X_Tfidf = Tfidf_vect.transform(frame['text_final'])
            frame[term] = list(SVM.predict(All_X_Tfidf))
        else:
            frame=0
    return frame
```

Section 1.2. Reading Manually Annotated Tweets and Conducting SVM Performance Test

```
# In[ ]:
# read mannually coded data
Corpus = pd.read_excel('/Users/ Dropbox/ BLM_mannual.xlsx',sheet_name="Twitter")

# In[ ]: Corpus
# In[ ]:
# list all the columns
Corpus_names=list(Corpus.columns)

# In[ ]:
# get the columns we want to analyze
term_list=Corpus_names[3:20]

# In[ ]:
def set_nan_zero(Corpus,term_list):
    for term in term_list:
        for i in range(len(Corpus)):
            if pd.isnull(Corpus.loc[i,term]):
                Corpus.loc[i,term]=0
    return Corpus

# set nan values to zero
Corpus=set_nan_zero(Corpus,term_list)
# In[ ]:
# define the useless words in twitter
twitter_stopwords=['http','bbc','news','cnn','type','gfgthfcg','gfhshz','app','ntdchinanewsdailybroad
cast','lee','gfrgrfgs']

# In[88]:
# parse twitter
Corpus=parse_text(Corpus,twitter_stopwords,'content')

# In[91]:
# performance test for coded twitter
svm_train(Corpus,term_list,0,'False')
```

Section 1.3. Reading Manually Annotated Newspaper Samples and Conducting SVM Performance Test

```
# In[37]:
Corpus_news = pd.read_excel('/Users/ Dropbox/ BLM_mannual.xlsx',sheet_name="newspaper")
# In[38]: Corpus_news
```

```
# In[39]:
# get the columns we want to analyze
Corpus_names=list(Corpus_news.columns)
#term_list=Corpus_names[7:36]
# In[40]: term_list=Corpus_names[4:]
# In[41]: Corpus_news=parse_text(Corpus_news,twitter_stopwords,'Text')
# In[42]: Corpus_news=set_nan_zero(Corpus_news,term_list)
# In[47]: Corpus_news
# In[44]:
# performance test for the coded news
svm_train(Corpus_news,term_list,0,'False')
```

Section 1.4. Reading Full Newspaper Sample and Coding Using SVM Algorithm

```
# In[ ]:
# read all the news
dr='/Users/Dropbox/Miscs/BLM_newspaper/'
medias=['NYT','WP','WSJ','BG','USA']
docs_all={}
for media in medias:
    appended_data = []
    directory=dr+media+'/'
    for filename in os.listdir(directory):
        filepath = directory+filename
        print(filepath)
        if ('.RTF' in filepath) and ('Best Sellers_ ' not in filepath):
            #print(filepath)
            fc_data = ne.nexis_rtf_extract(filepath)
            df_fc = ne.news_export(fc_data)
            appended_data.append(df_fc)
        elif '.txt' in filepath:
            fc_data = ne.factiva_extract(filepath)
            fc_converted = ne.fix_fac_fieldnames(fc_data)
            df_fc = ne.news_export(fc_converted)
            df_fc = df_fc.loc[:,~df_fc.columns.duplicated()]
            appended_data.append(df_fc)
    docs_all[media] = pd.concat(appended_data)
    docs_all[media] = docs_all[media].reset_index()

docs_news_list=[]
for media in medias:
    docs_news_list.append(docs_all[media])
```

```
docs_news=pd.concat(docs_news_list)
docs_news=docs_news.reset_index()

# In[ ]: docs_news
# In[94]:
# parse all news articles
docs_parsed=parse_text(docs_news,twitter_stopwords,'BODY')
# In[95]: docs_parsed
# In[96]:
# SVM coding
docs_coded=svm_train(Corpus_news,term_list,docs_parsed,True)
# In[97]:
# To identify which rows have at least two "1" values, sum up all values in each row
sum_rows=docs_coded[term_list[:-1]].sum(axis=1,numeric_only=True)
# In[98]:
# number of news with only 0 values
len(sum_rows[sum_rows==0])
# In[99]:
# number of news with only one 1 value
len(sum_rows[sum_rows==1])
# In[102]: docs_coded['sum']=docs_coded[term_list[:-1]].sum(axis=1,numeric_only=True)
# In[105]:
# all the news with only 0 values or only one 1 value
docs_uncoded=docs_coded[(docs_coded['sum']==0)|(docs_coded['sum']==1)]
# In[127]:
# all the news with at least two 1 values
docs_allcoded=docs_coded[(docs_coded['sum']!=0)&(docs_coded['sum']!=1)]
# In[128]:
docs_allcoded.to_excel('BLM_newspaper_allcoded.xlsx')
# In[100]: docs_coded.to_excel('BLM_newspaper_coded.xlsx')
# In[106]: docs_uncoded.to_excel('BLM_newspaper_uncoded.xlsx')
# In[ ]:
```

Section 1.5. Reading Full Twitter Sample and Coding Using SVM Algorithm

```
import numpy as np
import pandas as pd
import csv
import glob
import os
import matplotlib.pyplot as plt
import matplotlib as mpl
```

```
import seaborn as sns

Corpus = pd.read_excel('/scratch/jh126/BLM_mannual.xlsx',sheet_name="Twitter")

# get the columns we want to analyze
Corpus_names=list(Corpus.columns)
term_list=Corpus_names[3:20]

def set_nan_zero(Corpus,term_list):
    for term in term_list:
        for i in range(len(Corpus)):
            if pd.isnull(Corpus.loc[i,term]):
                Corpus.loc[i,term]=0
    return Corpus

# set nan cells to zero
Corpus=set_nan_zero(Corpus,term_list)
# read all tweets
#frame = pd.read_hdf('/scratch/jh126/blm_full.h5')
#frame =frame.reset_index(drop=True)
from nltk.tokenize import word_tokenize
from nltk import pos_tag
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.preprocessing import LabelEncoder
from collections import defaultdict
from nltk.corpus import wordnet as wn
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer
from sklearn import model_selection, naive_bayes, svm
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_recall_fscore_support
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from nltk.tokenize import TweetTokenizer
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, StratifiedKFold, cross_val_score
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, accuracy_score, f1_score
```

```
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import confusion_matrix, roc_auc_score, recall_score, precision_score

twitter_stopwords=['http','bbc','news','cnn','type','gfgthfcg','gfhshz','app','ntdchinanewsdailybroad
cast','lee','gfrgrfgs']

def parse_text(Corpus,twitter_stopwords,text_name='text'):
    '''Tokenize twitter/news texts and remove stop words
    Write the list of parsed words in the new column "text_final"'''
    # Step - a : Remove blank rows if any.
    #Corpus['text']=Corpus['text'].dropna(inplace=True)
    # Step - b : Change all the text to lower case. This is required as python interprets 'dog' and
'DOG' differently
    Corpus[text_name] = [str(entry).lower() for entry in Corpus[text_name]]
    # Step - c : Tokenization : In this each entry in the corpus will be broken into set of words
    Corpus[text_name]= [word_tokenize(entry) for entry in Corpus[text_name]]
    # Step - d : Remove Stop words, Non-Numeric and perfom Word Stemming/Lemmenting.
    # WordNetLemmatizer requires Pos tags to understand if the word is noun or verb or
adjective etc. By default it is set to Noun
    tag_map = defaultdict(lambda : wn.NOUN)
    tag_map['J'] = wn.ADJ
    tag_map['V'] = wn.VERB
    tag_map['R'] = wn.ADV
    for index,entry in enumerate(Corpus[text_name]):
        # Declaring Empty List to store the words that follow the rules for this step
        Final_words = []
        # Initializing WordNetLemmatizer()
        word_Lemmatized = WordNetLemmatizer()
        # pos_tag function below will provide the 'tag' i.e if the word is Noun(N) or Verb(V) or
something else.
        for word, tag in pos_tag(entry):
            # Below condition is to check for Stop words and consider only alphabets
            if word not in stopwords.words('english') and word.isalpha() and
word.encode('UTF-8').isalpha():
                if word not in twitter_stopwords:
                    word_Final = word_Lemmatized.lemmatize(word,tag_map[tag[0]])
                    Final_words.append(word_Final)
        # The final processed set of words for each iteration will be stored in 'text_final'
        Corpus.loc[index,'text_final'] = str(Final_words)
        with open('progress.txt', 'w') as f:
            f.write('%d' % index)
```

```
    return Corpus

def svm_train(Corpus,term_list,frame,predict,rnum):
    '''SVM Training
    Corpus: Manually coded parsed texts
    term_list the list of coded terms
    frame: Parsed texts to be coded. When predict==False, set it to 0
    predict: whether or not doing prediction'''
    conf_mat={}

    for term in term_list:
        #Train_X, Test_X, Train_Y, Test_Y =
model_selection.train_test_split(Corpus['text_final'],Corpus['Sovereignty
claim'],test_size=0.3,random_state=1)
        Train_X, Test_X, Train_Y, Test_Y =
model_selection.train_test_split(Corpus['text_final'],Corpus[term],test_size=0.3,random_state=r
num)

        Encoder = LabelEncoder()
        #Train_Y = Encoder.fit_transform(Train_Y.astype(str))
        #Test_Y = Encoder.fit_transform(Test_Y.astype(str))

        Tfidf_vect = TfidfVectorizer(max_features=5000)
        Tfidf_vect.fit(Corpus['text_final'])
        Train_X_Tfidf = Tfidf_vect.transform(Train_X)
        Test_X_Tfidf = Tfidf_vect.transform(Test_X)

        # Classifier - Algorithm - SVM
        # fit the training dataset on the classifier
        SVM = svm.SVC(C=1, kernel='linear', degree=3, gamma='auto')
        SVM.fit(Train_X_Tfidf,Train_Y)
        # predict the labels on validation dataset
        predictions_SVM = SVM.predict(Test_X_Tfidf)

        conf_mat[term] = confusion_matrix(Test_Y, predictions_SVM)
        # Use accuracy_score function to get the accuracy
        print(term)
        #print("SVM Accuracy Score -> ",accuracy_score(predictions_SVM, Test_Y)*100)
        print(precision_recall_fscore_support(predictions_SVM, Test_Y, average='weighted'))

        if predict==True:
```

```
            All_X_Tfidf = Tfidf_vect.transform(frame['text_final'])
            frame[term] = list(SVM.predict(All_X_Tfidf))
        else:
            frame=0
    return frame

Corpus=parse_text(Corpus,twitter_stopwords,'content')
frame = pd.read_hdf('blm_twi_parsed_3000000.h5')
frame =frame.reset_index(drop=True)
frame.text_final=frame.text_final.astype(str)
frame_real = frame.iloc[0:1000000]
frame_real['text_final']=frame.iloc[1000000:1000000*2]['text_final'].values
#for rnum in range(1,20):
frame_real = svm_train(Corpus,term_list,frame_real,True,1)
sum_rows=frame_real[term_list[:-1]].sum(axis=1,numeric_only=True)
total_rows = len(frame_real)
cx = total_rows - len(sum_rows[sum_rows==0]) - len(sum_rows[sum_rows==1])
#print('rows of at least two terms: ',cx,'rnum: ',rnum)
print('total rows: ',total_rows)
print('rows of at least two terms: ',cx)
frame_real.to_hdf('blm_twi_coded_3000000.h5', key='df', mode='w')
```

Section 2. Social Network Analysis

Section 2.1. R Script for Newspaper Network Visualization

```
library(readxl)
library(igraph)
library(ggplot2)
library(RColorBrewer)

data0<-read_excel('/Users/ Dropbox/ BLM_news_network.xlsx')
#data0<-read_excel('/Users/Dropbox/test_twitter.xlsx',sheet=1)
#replace NA to 0
#data0[is.na(data0)]<-0

data1<-read_excel('/Users/Dropbox/BLM_news_network_emotion.xlsx')
data1[is.na(data1)]<-0
topics<-data1
#year<-"2012"
# select articles in 2012
#rdate<-as.Date(data0$date, origin = "1970-01-01")
```

```
#data<-data0[data0$date>=paste(year,"-01-01",sep="") & data0$date<=paste(year,"-12-
31",sep=""),]

df<-aggregate(data0$weight,list(data0$term1,data0$term2),sum)
colnames(df)<-c("term1","term2","weight")

# create directed network based on df
net <- graph_from_data_frame(d=df,vertices=topics,directed=F)
# get degree of centrality of all nodes
deg<-degree(net,mode="all")
# node size is dependent on degree of centrality
V(net)$size<-(V(net)$`total`)^0.48
# Generate vertice colors based on negative proportion
#palf <- colorRampPalette(c("steelblue1","indianred2"))
coul <- brewer.pal(n = 11, name = 'RdBu')
palf <- colorRampPalette(coul[7:9])
V(net)$color<-palf(100)[as.numeric(cut(V(net)$`emotion`,breaks = 100))]
#V(net)$color<-coul[as.numeric(cut(V(net)$`emotion`,breaks = 100))]
V(net)$label.cex<-0.65
V(net)$label.color="black"
#E(net)$arrow.size<-E(net)$weight*.1
# edge width based on weight
E(net)$width <- (E(net)$weight)^0.32

#E(net)$color <- adjustcolor(colrs[E(net)$valance],alpha.f=.7)
# Edge label based on width, but + sign before pos valence, - sign before neg valance
vsign<-c("+","-","")
#E(net)$label<-
ifelse(abs(E(net)$weight)==1,paste(vsign[E(net)$valance],E(net)$weight,sep=""),NA)
#E(net)$label<-paste(vsign[E(net)$valance],E(net)$weight,sep="")
#E(net)$label.cex=0.8

pdf(paste("/Users/Dropbox/BLM_news.pdf",sep=""))
#plot(net,layout=layout_with_kk(net,weights=(E(net)$weight)^0.4*2),main=paste("Twitter"),ed
ge.curved=.3)
plot(net,layout=layout_with_dh,edge.curved=.0,arrow.mode=0)
#plot(net,main=paste("China",year),edge.curved=.25)

#plot(net,main=paste("China",year))
dev.off()
```

Section 2.2. R Script for Twitter Network Visualization

```
library(readxl)
library(igraph)
library(ggplot2)
library(RColorBrewer)

data0<-read.csv('/Users/Dropbox/BLM_twitter_network.csv')
#data0<-read_excel('/Users/Dropbox/test_twitter.xlsx',sheet=1)
#replace NA to 0
#data0[is.na(data0)]<-0

data1<-read_excel('/Users/ Dropbox/ BLM_twitter_network_emotion.xlsx')
data1[is.na(data1)]<-0
topics<-data1
#year<-"2012"
# select articles in 2012
#rdate<-as.Date(data0$date, origin = "1970-01-01")
#data<-data0[data0$date>=paste(year,"-01-01",sep="") & data0$date<=paste(year,"-12-
31",sep=""),]
df<-aggregate(data0$weight,list(data0$term1,data0$term2),sum)
colnames(df)<-c("term1","term2","weight")
# create directed network based on df
net <- graph_from_data_frame(d=df,vertices=topics,directed=F)
# get degree of centrality of all nodes
deg<-degree(net,mode="all")
# node size is dependent on degree of centrality
V(net)$size<-((V(net)$`total`)/100)^0.44
# Generate vertice colors based on negative proportion
#palf <- colorRampPalette(c("steelblue1","indianred2"))
coul <- brewer.pal(n = 11, name = 'RdBu')
palf <- colorRampPalette(coul[3:5])
V(net)$color<-palf(100)[as.numeric(cut(V(net)$`emotion`,breaks = 100))]
#V(net)$color<-coul[as.numeric(cut(V(net)$`emotion`,breaks = 100))]
V(net)$label.cex<-0.65
V(net)$label.color="black"
#E(net)$arrow.size<-E(net)$weight*.1
# edge width based on weight
E(net)$width <- ((E(net)$weight)/100)^0.32
#E(net)$color <- adjustcolor(colrs[E(net)$valance],alpha.f=.7)
# Edge label based on width, but + sign before pos valence, - sign before neg valance
vsign<-c("+","-","")
```

```
#E(net)$label<-
ifelse(abs(E(net)$weight)==1,paste(vsign[E(net)$valance],E(net)$weight,sep=""),NA)
#E(net)$label<-paste(vsign[E(net)$valance],E(net)$weight,sep="")
#E(net)$label.cex=0.8
pdf(paste("/Users/ Dropbox/ BLM_twitter.pdf",sep=""))
#plot(net,layout=layout_with_kk(net,weights=(E(net)$weight)^0.4*2),main=paste("Twitter"),ed
ge.curved=.3)
plot(net,layout=layout_with_dh,edge.curved=.0,arrow.mode=0)
#plot(net,main=paste("China",year),edge.curved=.25)
```

Section 3. Time Series Analysis

```
#!/usr/bin/env python
# coding: utf-8
# In[2]:
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import grangercausalitytests
from statsmodels.tsa.arima_model import ARMA
get_ipython().run_line_magic('matplotlib', 'inline')
```

Section 3.1. Reading and Preprocessing Data

```
# In[3]:
# Load twitter and newspaper
#df_news = pd.read_hdf('mask_news_coded.h5')
df_twi = pd.read_hdf('blm_twi_allcoded.h5')
# In[4]: df_news = pd.read_excel('BLM_newspaper_allcoded.xlsx')
# In[5]: df_twi
# In[6]: df_news
# In[9]: df_news['date']=pd.to_datetime(df_news['DATE'])
df_twi['date']=pd.to_datetime(df_twi['date'])
# In[20]: df_twi['date']=df_twi['date'].dt.tz_convert(None)
# In[7]: # get the columns we want to analyze
df_twi_names=list(df_twi.columns)
term_list=df_twi_names[1:18]
# In[8]:term_list
# In[10]: def set_nan_zero(Corpus,term_list):
    for term in term_list:
        for i in range(len(Corpus)):
```

```
            if pd.isnull(Corpus.loc[i,term]):
                Corpus.loc[i,term]=0
    return Corpus

# In[11]: df_news=set_nan_zero(df_news,term_list)
# In[12]: for j in range(len(term_list[0:20])):
    dft_sub = df_twi.loc[df_twi[term_list[j]]==1]
    df_sub = df_news.loc[df_news[term_list[j]]==1]
    print(term_list[j],len(dft_sub),len(df_sub))
    #print(topic_list[j],len(df_sub))
# In[13]: def GC_test(df_news,df_twi,topic_list,date_start,date_end):
    coef={}
    pval={}
    adfc={}
    adfp={}
    for j in range(len(topic_list)):
        coef[topic_list[j]]={}
        pval[topic_list[j]]={}
        adfc[topic_list[j]]={}
        adfp[topic_list[j]]={}
        all_dates=pd.date_range(start=date_start, end=date_end)
        df_sub = df_news.loc[df_news[topic_list[j]]==1]
        dft_sub = df_twi.loc[df_twi[topic_list[j]]==1]
        news_series=np.zeros((len(all_dates)-1,2))
        for i in range(len(all_dates)-1):
            mask = (df_sub['date'] >= all_dates[i]) & (df_sub['date'] < all_dates[i+1])
            news_series[i,1]=len(df_sub.loc[mask])
            mask2 = (dft_sub['date'] >= all_dates[i]) & (dft_sub['date'] < all_dates[i+1])
            news_series[i,0]=len(dft_sub.loc[mask2])

        for i in range(2):
            if not all(news_series[:,i]==0.):
                mod = ARMA(news_series[:,i], order=(2,0))
                res = mod.fit()
                news_series[:,i]=res.resid

        #news_diff=np.diff(news_series,axis=0)
        result = adfuller(news_series[:,0])
        adfc[topic_list[j]]['twitter']=result[0]
        adfp[topic_list[j]]['twitter']=result[1]
        print(result[0],result[1])
```

```
            result = adfuller(news_series[:,1])
            print(result[0],result[1])
            adfc[topic_list[j]]['media']=result[0]
            adfp[topic_list[j]]['media']=result[1]
            res=grangercausalitytests(news_series,1)
            coef[topic_list[j]]['media']=res[1][1][1].params[1]
            pval[topic_list[j]]['media']=res[1][0]['ssr_ftest'][1]
            news_series2=np.roll(news_series, 1, axis=1)
            res=grangercausalitytests(news_series2,1)
            coef[topic_list[j]]['twitter']=res[1][1][1].params[1]
            pval[topic_list[j]]['twitter']=res[1][0]['ssr_ftest'][1]
        coef_themes=pd.DataFrame.from_dict(coef,orient='index')
        pval_themes=pd.DataFrame.from_dict(pval,orient='index')
        adfc_themes=pd.DataFrame.from_dict(adfc,orient='index')
        adfp_themes=pd.DataFrame.from_dict(adfp,orient='index')
        final_result={}
        final_result['coef']=coef_themes
        final_result['pval']=pval_themes
        final_result['adfc']=adfc_themes
        final_result['adfp']=adfp_themes
        return final_result

# In[41]: def GC_test_scale(df_news,df_twi,topic_list,date_start,date_end):
        coef={}
        pval={}
        adfc={}
        adfp={}
        for j in range(len(topic_list)):
            coef[topic_list[j]]={}
            pval[topic_list[j]]={}
            adfc[topic_list[j]]={}
            adfp[topic_list[j]]={}
            all_dates=pd.date_range(start=date_start, end=date_end)
            #df_sub = df_news.loc[df_news[topic_list[j]]==1]
            #dft_sub = df_twi.loc[df_twi[topic_list[j]]==1]
            news_series=np.zeros((len(all_dates)-1,2))
            for i in range(len(all_dates)-1):
                mask = (df_news['date'] >= all_dates[i]) & (df_news['date'] < all_dates[i+1])
                df_sub=df_news.loc[mask]
                df_sub_mean=df_sub[topic_list[j]].mean(skipna=True)
                news_series[i,1]=df_sub_mean
```

```
            mask2 = (df_twi['date'] >= all_dates[i]) & (df_twi['date'] < all_dates[i+1])
            dft_sub=df_twi.loc[mask2]
            dft_sub_mean=dft_sub[topic_list[j]].mean(skipna=True)
            news_series[i,0]=dft_sub_mean
        for i in range(2):
            if not all(news_series[:,i]==0.):
                mod = ARMA(news_series[:,i], order=(2,0))
                res = mod.fit()
                news_series[:,i]=res.resid
        #news_diff=np.diff(news_series,axis=0)
        result = adfuller(news_series[:,0])
        adfc[topic_list[j]]['twitter']=result[0]
        adfp[topic_list[j]]['twitter']=result[1]
        print(result[0],result[1])
        result = adfuller(news_series[:,1])
        print(result[0],result[1])
        adfc[topic_list[j]]['media']=result[0]
        adfp[topic_list[j]]['media']=result[1]
        res=grangercausalitytests(news_series,1)
        coef[topic_list[j]]['media']=res[1][1][1].params[1]
        pval[topic_list[j]]['media']=res[1][0]['ssr_ftest'][1]
        news_series2=np.roll(news_series, 1, axis=1)
        res=grangercausalitytests(news_series2,1)
        coef[topic_list[j]]['twitter']=res[1][1][1].params[1]
        pval[topic_list[j]]['twitter']=res[1][0]['ssr_ftest'][1]

    coef_themes=pd.DataFrame.from_dict(coef,orient='index')
    pval_themes=pd.DataFrame.from_dict(pval,orient='index')
    adfc_themes=pd.DataFrame.from_dict(adfc,orient='index')
    adfp_themes=pd.DataFrame.from_dict(adfp,orient='index')
    final_result={}
    final_result['coef']=coef_themes
    final_result['pval']=pval_themes
    final_result['adfc']=adfc_themes
    final_result['adfp']=adfp_themes
    return final_result,news_series
```

Section 3.2. Granger Causality Test for Substantive Attributes

```
# In[21]: GC_res=GC_test(df_news,df_twi,term_list,'5/25/20','11/03/20')
# In[22]: GC_res['coef']
# In[23]: GC_res['pval']
```

Section 3.3. Granger Causality Test for Affective Attributes

```
# In[42]: GC_res, emotion=GC_test_scale(df_news,df_twi,[term_list[-1]],'5/27/20','11/03/20')
# In[43]: GC_res['coef']
# In[44]: GC_res['pval']
```

Section 3.4. Granger Causality Test for Substantive Attributes Combined with Affective Attributes

```
# In[56]: def GC_test_emotion_term(df_news,df_twi,topic_list,emotion,date_start,date_end):
    coef={}
    pval={}
    adfc={}
    adfp={}
    for j in range(len(topic_list)):
        print(topic_list[j])
        coef[topic_list[j]]={}
        pval[topic_list[j]]={}
        adfc[topic_list[j]]={}
        adfp[topic_list[j]]={}

        all_dates=pd.date_range(start=date_start, end=date_end)

        df_sub = df_news.loc[df_news[topic_list[j]]==1]
        dft_sub = df_twi.loc[df_twi[topic_list[j]]==1]

        news_series=np.zeros((len(all_dates)-1,2))
        for i in range(len(all_dates)-1):
            mask = (df_sub['date'] >= all_dates[i]) & (df_sub['date'] < all_dates[i+1])
            df_sub_item=df_sub.loc[mask]
            df_sub_mean=df_sub_item[emotion].mean(skipna=True)
            news_series[i,1]=df_sub_mean

            mask2 = (dft_sub['date'] >= all_dates[i]) & (dft_sub['date'] < all_dates[i+1])
            dft_sub_item=dft_sub.loc[mask2]
            dft_sub_mean=dft_sub_item[emotion].mean(skipna=True)
            news_series[i,0]=dft_sub_mean

        news_series=news_series[~np.isnan(news_series).any(axis=1),:]

        for i in range(2):
            if not all(news_series[:,i]==0.):
```

```
                mod = ARMA(news_series[:,i], order=(2,0))
                res = mod.fit()
                news_series[:,i]=res.resid

        #news_diff=np.diff(news_series,axis=0)
        result = adfuller(news_series[:,0])
        adfc[topic_list[j]]['twitter']=result[0]
        adfp[topic_list[j]]['twitter']=result[1]
        print(result[0],result[1])
        result = adfuller(news_series[:,1])
        print(result[0],result[1])
        adfc[topic_list[j]]['media']=result[0]
        adfp[topic_list[j]]['media']=result[1]

        res=grangercausalitytests(news_series,1)
        coef[topic_list[j]]['media']=res[1][1][1].params[1]
        pval[topic_list[j]]['media']=res[1][0]['ssr_ftest'][1]

        news_series2=np.roll(news_series, 1, axis=1)

        res=grangercausalitytests(news_series2,1)
        coef[topic_list[j]]['twitter']=res[1][1][1].params[1]
        pval[topic_list[j]]['twitter']=res[1][0]['ssr_ftest'][1]

    coef_themes=pd.DataFrame.from_dict(coef,orient='index')
    pval_themes=pd.DataFrame.from_dict(pval,orient='index')
    adfc_themes=pd.DataFrame.from_dict(adfc,orient='index')
    adfp_themes=pd.DataFrame.from_dict(adfp,orient='index')

    final_result={}
    final_result['coef']=coef_themes
    final_result['pval']=pval_themes
    final_result['adfc']=adfc_themes
    final_result['adfp']=adfp_themes

    return final_result

# In[58]: GC_res =GC_test_emotion_term(df_news,df_twi,term_list[:-1],term_list[-
1],'5/27/20','11/03/20')

# In[60]: GC_res['coef']
```

In[59]: GC_res['pval']

Section 3.5. Granger Causality Test for Bundled Substantive Attributes

```
# In[61]: term_list
# In[146]: comb_list=['police & policing - violence','killing of Floyd - police & policing',
          'Demonstration & protest - police & policing','Demonstration & protest - violence',
          'Police & policing - systemic racism',
          'Violence - systemic racism', 'The 2020 Election - American politics']
# In[147]:
comb_item_list=[]
comb_item_list.append([term_list[3],term_list[5]])
comb_item_list.append([term_list[0],term_list[3]])
comb_item_list.append([term_list[2],term_list[3]])
comb_item_list.append([term_list[2],term_list[5]])
comb_item_list.append([term_list[3],term_list[6]])
comb_item_list.append([term_list[5],term_list[6]])
comb_item_list.append([term_list[1],term_list[7]])

# In[143]: comb_item_list
# In[67]:
def GC_test_multi(df_news,df_twi,topic_list,items_list,date_start,date_end):
    coef={}
    pval={}
    adfc={}
    adfp={}
    for j in range(len(topic_list)):
        coef[topic_list[j]]={}
        pval[topic_list[j]]={}
        adfc[topic_list[j]]={}
        adfp[topic_list[j]]={}
        all_dates=pd.date_range(start=date_start, end=date_end)
        if len(items_list[j])==2:
            con_news = (df_news[items_list[j][0]]==1) & (df_news[items_list[j][1]]==1)
            con_twi = (df_twi[items_list[j][0]]==1) & (df_twi[items_list[j][1]]==1)
        elif len(items_list[j])==3:
            con_news = (df_news[items_list[j][0]]==1) & (df_news[items_list[j][1]]==1) &
(df_news[items_list[j][2]]==1)
            con_twi = (df_twi[items_list[j][0]]==1) & (df_twi[items_list[j][1]]==1) &
(df_twi[items_list[j][2]]==1)
        else: print('We only support combinations of two and three items')
```

```
        df_sub = df_news.loc[con_news]
        dft_sub = df_twi.loc[con_twi]
        news_series=np.zeros((len(all_dates)-1,2))
        for i in range(len(all_dates)-1):
            mask = (df_sub['date'] >= all_dates[i]) & (df_sub['date'] < all_dates[i+1])
            news_series[i,1]=len(df_sub.loc[mask])
            mask2 = (dft_sub['date'] >= all_dates[i]) & (dft_sub['date'] < all_dates[i+1])
            news_series[i,0]=len(dft_sub.loc[mask2])
        news_series=news_series[~np.isnan(news_series).any(axis=1),:
        for i in range(2):
            if not all(news_series[:,i]==0.):
                mod = ARMA(news_series[:,i], order=(2,0))
                res = mod.fit()
                news_series[:,i]=res.resid

        #news_diff=np.diff(news_series,axis=0)
        result = adfuller(news_series[:,0])
        adfc[topic_list[j]]['twitter']=result[0]
        adfp[topic_list[j]]['twitter']=result[1]
        print(result[0],result[1])
        result = adfuller(news_series[:,1])
        print(result[0],result[1])
        adfc[topic_list[j]]['media']=result[0]
        adfp[topic_list[j]]['media']=result[1]
        res=grangercausalitytests(news_series,1)
        coef[topic_list[j]]['media']=res[1][1][1].params[1]
        pval[topic_list[j]]['media']=res[1][0]['ssr_ftest'][1]
        news_series2=np.roll(news_series, 1, axis=1)
        res=grangercausalitytests(news_series2,1)
        coef[topic_list[j]]['twitter']=res[1][1][1].params[1]
        pval[topic_list[j]]['twitter']=res[1][0]['ssr_ftest'][1]

    coef_themes=pd.DataFrame.from_dict(coef,orient='index')
    pval_themes=pd.DataFrame.from_dict(pval,orient='index')
    adfc_themes=pd.DataFrame.from_dict(adfc,orient='index')
    adfp_themes=pd.DataFrame.from_dict(adfp,orient='index')

    final_result={}
    final_result['coef']=coef_themes
    final_result['pval']=pval_themes
    final_result['adfc']=adfc_themes
```

```
        final_result['adfp']=adfp_themes
        return final_result
# In[148]:
GC_res=GC_test_multi(df_news,df_twi,comb_list,comb_item_list,'5/25/20','11/03/20')
# In[149]: GC_res['coef']
# In[150]: GC_res['pval']
```

Section 3.6. Granger Causality Test for Bundled Substantive Attributes Combined with Affective Attributes

```
# In[72]:
def
GC_test_emotion_term_multi(df_news,df_twi,topic_list,items_list,emotion,date_start,date_end):
        coef={}
        pval={}
        adfc={}
        adfp={}
        for j in range(len(topic_list)):
                print(topic_list[j])
                coef[topic_list[j]]={}
                pval[topic_list[j]]={}
                adfc[topic_list[j]]={}
                adfp[topic_list[j]]={}

                all_dates=pd.date_range(start=date_start, end=date_end)

                if len(items_list[j])==2:
                        con_news = (df_news[items_list[j][0]]==1) & (df_news[items_list[j][1]]==1)
                        con_twi = (df_twi[items_list[j][0]]==1) & (df_twi[items_list[j][1]]==1)
                elif len(items_list[j])==3:
                        con_news = (df_news[items_list[j][0]]==1) & (df_news[items_list[j][1]]==1) &
(df_news[items_list[j][2]]==1)
                        con_twi = (df_twi[items_list[j][0]]==1) & (df_twi[items_list[j][1]]==1) &
(df_twi[items_list[j][2]]==1)
                else:
                        print('We only support combinations of two and three items')

                df_sub = df_news.loc[con_news]
                dft_sub = df_twi.loc[con_twi]

                news_series=np.zeros((len(all_dates)-1,2))
                for i in range(len(all_dates)-1):
```

```
            mask = (df_sub['date'] >= all_dates[i]) & (df_sub['date'] < all_dates[i+1])
            df_sub_item=df_sub.loc[mask]
            df_sub_mean=df_sub_item[emotion].mean(skipna=True)
            news_series[i,1]=df_sub_mean

            mask2 = (dft_sub['date'] >= all_dates[i]) & (dft_sub['date'] < all_dates[i+1])
            dft_sub_item=dft_sub.loc[mask2]
            dft_sub_mean=dft_sub_item[emotion].mean(skipna=True)
            news_series[i,0]=dft_sub_mean

        news_series=news_series[~np.isnan(news_series).any(axis=1),:]

        for i in range(2):
            if not all(news_series[:,i]==0.):
                mod = ARMA(news_series[:,i], order=(2,0))
                res = mod.fit()
                news_series[:,i]=res.resid

        #news_diff=np.diff(news_series,axis=0)
        result = adfuller(news_series[:,0])
        adfc[topic_list[j]]['twitter']=result[0]
        adfp[topic_list[j]]['twitter']=result[1]
        print(result[0],result[1])
        result = adfuller(news_series[:,1])
        print(result[0],result[1])
        adfc[topic_list[j]]['media']=result[0]
        adfp[topic_list[j]]['media']=result[1]

        res=grangercausalitytests(news_series,1)
        coef[topic_list[j]]['media']=res[1][1][1].params[1]
        pval[topic_list[j]]['media']=res[1][0]['ssr_ftest'][1]

        news_series2=np.roll(news_series, 1, axis=1)

        res=grangercausalitytests(news_series2,1)
        coef[topic_list[j]]['twitter']=res[1][1][1].params[1]
        pval[topic_list[j]]['twitter']=res[1][0]['ssr_ftest'][1]

    coef_themes=pd.DataFrame.from_dict(coef,orient='index')
    pval_themes=pd.DataFrame.from_dict(pval,orient='index')
    adfc_themes=pd.DataFrame.from_dict(adfc,orient='index')
```

```
    adfp_themes=pd.DataFrame.from_dict(adfp,orient='index')

    final_result={}
    final_result['coef']=coef_themes
    final_result['pval']=pval_themes
    final_result['adfc']=adfc_themes
    final_result['adfp']=adfp_themes

    return final_result

# In[151]:
GC_res=GC_test_emotion_term_multi(df_news,df_twi,comb_list,comb_item_list,term_list[-1],'5/27/20','11/03/20')
# In[152]: GC_res['coef']
# In[153]: GC_res['pval']
```

Section 3.7. Data Preparation for Node and Edge in NAS Analysis

```
# In[76]: from itertools import combinations
# In[77]: term_list
# In[135]:
comb = list(combinations(term_list[:-1],2))
edge_list_news=[]
comb1_list=[]
comb2_list=[]
i=0
term1_list=[]
term2_list=[]
len12_list=[]
for icomb in comb:
    term1=icomb[0]
    term2=icomb[1]
    len12=len(df_news.loc[(df_news[term1]==1)&(df_news[term2]==1)])
    comb1_list.append(term1)
    comb2_list.append(term2)
    edge_list_news.append(len12)
    for i in range(len12):
        term1_list.append(term1)
        term2_list.append(term2)
        len12_list.append(1)

d = {'term1': term1_list, 'term2': term2_list, 'weight': len12_list}
```

```
df_news_network = pd.DataFrame(data=d)
de = {'term1': comb1_list, 'term2': comb2_list, 'edge': edge_list_news}
df_news_network_edge = pd.DataFrame(data=de)

# In[136]:
df_news_network.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)
df_news_network_edge.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)

# In[112]: df_news_network
# In[137]: df_news_network_edge
# In[118]:
emotion_list_news=[]
total_no_list_news=[]
for term in term_list[:-1]:
	emotion_list_news.append(df_news.loc[(df_news[term]==1)][term_list[-
1]].mean(skipna=True))
	total_no_list_news.append(len(df_news.loc[(df_news[term]==1)]))
d = {'term': term_list[:-1], 'emotion': emotion_list_news,'total':total_no_list_news}
df_news_network_emo = pd.DataFrame(data=d)

# In[119]:
df_news_network_emo.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)

# In[120]: df_news_network_emo
# In[121]: df_news_network_emo.to_excel('BLM_news_network_emotion.xlsx',index=False)
# In[138]: df_news_network_edge.to_excel('BLM_news_network_edge.xlsx',index=False)
# In[117]: df_news_network.to_excel('BLM_news_network.xlsx',index=False)
# In[139]:
i=0
edge_list_twi=[]
comb1_list=[]
comb2_list=[]
term1_list=[]
term2_list=[]
len12_list=[]
for icomb in comb:
	term1=icomb[0]
	term2=icomb[1]
```

```
        len12=len(df_twi.loc[(df_twi[term1]==1)&(df_twi[term2]==1)])

        comb1_list.append(term1)
        comb2_list.append(term2)
        edge_list_twi.append(len12)

        for i in range(len12):
            term1_list.append(term1)
            term2_list.append(term2)
            len12_list.append(1)

d = {'term1': term1_list, 'term2': term2_list, 'weight': len12_list}
df_twi_network = pd.DataFrame(data=d)
de = {'term1': comb1_list, 'term2': comb2_list, 'edge': edge_list_twi}
df_twi_network_edge = pd.DataFrame(data=de)

# In[140]:
df_twi_network.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)
df_twi_network_edge.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)
# In[123]:
df_twi_network.to_csv('BLM_twitter_network.csv',index=False)
# In[132]:
emotion_list_twi=[]
total_no_list_twi=[]
for term in term_list[:-1]:
    emotion_list_twi.append(df_twi.loc[(df_twi[term]==1)][term_list[-1]].mean(skipna=True))
    total_no_list_twi.append(len(df_twi.loc[(df_twi[term]==1)]))
d = {'term': term_list[:-1], 'emotion': emotion_list_twi, 'total':total_no_list_twi}
df_twi_network_emo = pd.DataFrame(data=d)
# In[133]:
df_twi_network_emo.replace({'Death of Floyd': 'Killing of Floyd', 'Civic Movements': 'Cancel
Culture','Legal System':'Justice & Legal System'},inplace=True)
# In[134]: df_twi_network_emo.to_excel('BLM_twitter_network_emotion.xlsx',index=False)
# In[141]: df_twi_network_edge.to_excel('BLM_twitter_network_edge.xlsx',index=False)
# In[ ]:
```

APPENDIX B: QUALITATIVE INTERVIEW PROTOCAL

Opening Remarks:

First of all, I would like to express my appreciation for your kind participation in this interview. Before I start the interview, I would like to briefly walk you through what I am hoping to learn from you today. I would also like to provide you some general disclaimers as to the procedure of this interview.

This is a research using mixed methodology to examine the agenda interplay between newspapers and Twitter, using the Black Lives Matter movement as a case study. Interviews with journalists constitute the second section of this research, which is used to make better sense of the results of my big data analysis. Specifically, the purpose of this interview is to learn more about your insights into the impact of Twitter on your routine as a journalist. This interview will last 20 – 30 minutes, and the contents of this interview maybe used within my final project, which I intend to use in my final doctoral dissertation project and possibly for the purposes of presenting at an academic conference or publishing in peer-reviewed scholarly journals.

Next, I would like to reiterate your rights as a participant. This project has been certified as exempt by the Institutional Review Board of the Washington State University. Your participation in this research project is completely voluntary, and your responses will be kept confidential. No personally identifiable information will be associated with your responses in any reports of these data. In essence, I will anonymize all respondents and their contact information in my research paper. Also, please note that your participation in this interview is completely voluntary, and you are free to stop or leave this interview at any point in time during the process. Choosing to do so will not impact your relationship with the researcher or Washington State University. Also, if there are any questions that you don't feel comfortable responding, please also feel free to let me know and I will make sure to skip those questions.

I will be recording this interview with a voice recorder. I will also be taking notes throughout the interview. The interview recording and my notes will be transcribed later on. Upon completion of my transcript, the original recordings and my notes will be destroyed. As mentioned earlier, you are guaranteed anonymity through the entire process. You will be assigned a pseudonym during transcription, such as "interviewee A," which guarantees that you will not be identifiable in my transcript and notes. You will have access to the findings following completion of this study.

Do you have any questions for me before I start this interview?

Great. Could I have your verbal consent to record this interview?

Awesome. Thank you again for agreeing to participate. Let's get into the first question.

Qualitative Interview Questions

1. How often do you use Twitter?
2. What is your primary purpose of using Twitter?
   - Probe: Do you think you have achieved the purpose?
3. Have you ever used Twitter for sourcing?
   a. If so, how did you incorporate the source on Twitter in your stories?
   b. If not, why?
4. Do public opinions on Twitter affect your choice of topics to report?
   a. If so, how have they affected you?
   - Probe: what were your motivations to choose a topic with the help of public opinions in the Twittersphere?
   b. If not, what were your motivations to not been affected?
5. Do public sentiments on Twitter affect your storytelling?
   a. If so, how have they affected you?
   - Probe: what were your motivation to incorporate or reflect the public sentiments in Twittersphere in your own stories?
   b. If not, why haven't you incorporated or reflected the public sentiments you saw from the Twittersphere in your stories?
6. In general, how has Twitter changed your work routines and your published work?
7. In general, how has Twitter changed the professional norms in the news industry?

8. In general, how do you evaluate the pros and cons of Twitter's impact on traditional journalism, respectively?

Closing Remarks:

That concludes our interview. Thank you very much for your time. This interview will definitely help me move my research forward. I look forward to going over his interview and possibly speaking to you again in the future. Please do not hesitate to contact me if you have any questions or concerns.

APPENDIX C: QUALITATIVE INTERVIEW CODEBOOK

Code	Definition	Examples (from the transcript)
FREQ	The frequency with which a journalist uses Twitter.	1. "Like, everyday." 2. "Completely. I almost always have a Twitter tab open as I work, scrolling through to stay updated on the day's major stories, and the internet's reactions."
PURP	The journalist's primary purpose of using Twitter.	"you know, one of my primary purposes of using Twitter is to update the public on developing stories."
SOURCE	The journalist has used Twitter for sourcing.	"Like, I can trace an online trend, like Bernie Sander's viral mittens, back to its source, or I can survey real-time reactions to world events."
SUB	The journalist has been inspired by or adopted the trending topics discussed heatedly in the Twittersphere.	"…Not until this year did I include public comments on Twitter and Instagram as valid sources within stories."
AFF	The journalist has been inspired by or adopted the public sentiments in the Twittersphere.	"…the tools for understanding public sentiments have always been imperfect. Any individual journalist can only interview so many people directly. Journalists all must have other methods for generalizing about the feelings of a large mass of people. Twitter is one such method, I guess."
IMPACT1	The journalist's insights into Twitter's impact on their work routines and published works.	"For me, Twitter is mostly an efficient way to read the news. Twitter's addictive nature can sometimes make it a waste of time, a way to make me feel like I'm doing work when in fact I am gaining nothing from it."
IMPACT2	The journalist's insights into Twitter's impact on the professional norms in the news industry.	1. "For the most part, it seems to me that the expectation is to tweet out each of your stories, or if you're a breaking news reporter, perhaps the ones you're most proud of, as they're published. It's a form of updating your professional social circle as to where you are and what you're up to."

		2. “It has also become much more common, and in fact encouraged by many news outlets for journalists to promote their own work and their own brands on Twitter.”
PRO	The journalist’s insights into the positive sides of Twitter’s impact on traditional journalism.	“It is good because it is large, fast, and has tools, like hashtags, that allow for analysis.”
CON	The journalist’s insights into the dark sides of Twitter’s impact on traditional journalism.	“It feels to me that journalists increasingly risk viewing Twitter as reflective of the world at large, when it is, in fact, far from it. The more "online" journalists become, the more we shift our viewpoints toward those similar to us, with resources and access to internet culture.”