THE DYNAMICS OF PUBLIC ATTENTION TO CLIMATE CHANGE IN A HYBRID MEDIA SYSTEM

By

Yingying Chen

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ABSTRACT

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The dissertation is about the dynamics of public attention in the contemporary media system. What shapes the dynamics of public attention to a social issue across media over time is the primary empirical question that guides the following chapters. Nearly 50 years ago, Downs proposed the now-classic issue attention cycle, which explains the evolution of public attention. His issue attention cycle, along with traditional communication theories, such as agenda setting theory, agenda building theory, and gatekeeping theory, have suggested that a small group of elite organizational actors create and shape public attentiveness to social issues. However, more scholars question whether these traditional media theories can explain the evolution of public attention in today's media system. These scholars challenge the present applicability or appropriateness of these theories. To move forward current theories about public attention, this dissertation examines the conceptualization and causes of public attention by synthesizing literature from agenda setting, agenda building, and gatekeeping and information diffusion studies. Setting climate change as an analysis background, this dissertation unfolds with three empirical studies and realizes three research goals: (1) to clarify what public attention is and propose a robust way to measure it, (2) to disaggregate and typologize the attention from different types of actors on Twitter, and (3) to examine the patterns of public attention across different climate-related events. Findings suggest that: (1) Public attention is conceptually and empirically different from news attention, public opinion, and Twitter attention. Public attention

is less volatile, intensive and responsive to the real-life events in contrasting to the news attention and Twitter attention. (2) In terms of the relationship between attention from news, Twitter, and strategic organizations across mass media and digital media over time, Twitter attention is the most volatile and intensive comparing to news, public attention, and public opinion. The impact of strategic organizational attention (measured by press releases) exists at the daily level but does not sustain at the monthly level. (3) In terms of the transmedia diffusion of climate change attention, organizational actors in general are the source and individual actors are the spreaders of attention. Dynamic networks analysis show that individual actors sometimes become the top sources. (4) The event contexts play a role in determining who leads public attention.

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CHAPTER 1: INTRODUCTION

This dissertation is about public attention in the contemporary hybrid media system. Specifically, this study explores the primary question: What shapes the dynamics of public attention to a social issue across media outlets over time? At first glance, this question seems outdated. Nearly 50 years ago, Downs proposed the now-classic issue attention cycle model, which explains the evolution of public attention. His issue attention cycle, along with traditional communication theories, such as McCombs and Shaw's (1972) agenda setting theory, Turk and Franklin's (1987) agenda building theory, and Shoemaker's (1991) gatekeeping theory, have suggested that mainstream organizations (e.g., news media, political elites, governments, and other large organizations) shape public attention. These theories all suggest that a small group of elite organizational actors create and shape public attentiveness to issues (Neuman, 2016).

Numerous empirical studies have applied these communication theories to explain the dynamics of public attention in the context of digital media (e.g., Guggenheim et al., 2015; Jang et al., 2017). Meanwhile, other studies contend that although scholars developed these theories amid the era of mass media, these theories can still help explain the dynamics of public attention in the contemporary media system (see e.g., Djerf-Pierre & Shehata, 2017; Leskovec, Backstrom, & Kleinberg, 2009). However, more scholars question whether these traditional media theories can explain the evolution of public attention in today's media system (see e.g., Bennett & Iyengar, 2008; Neuman et al., 2014; Schroeder, 2018).

These scholars challenge the present applicability or appropriateness of these theories for several reasons. First, today's media environment values public attention, not just media attention; indeed, public attention is a valuable resource which different sets of actors compete to secure (Davenport & Beck, 2001; Tufekci, 2013; Webster, 2011). In the age of information, the proliferation of media and communication technologies enable exponentially more and more discourse, images, and spectacles (Citten, 2017), but humans' bandwidth of public attention has not grown (and arguably cannot grow) in step with the increasing content available for consumption (Hilgartner & Bosk, 1988). In fact, public attention rarely grows much (Edy & Meirick, 2018). Lehman (2007), an attention economist, pointed out that although within the digital space, there is seemingly a ceaseless supply of information, "attention is [a] commodity in short supply" (p.1). In other words, attention is the currency of today's media system (Zhang, Wells, Wang, & Rohe, 2018). Gaining public attention creates a gateway for organizations to advance their social, economic, and political values (Webster, 2011). For example, the success of a social movement depends on the extent to which advocacy groups can raise public attention to about the issue at hand (Thrall et al., 2014; Tufekci, 2013).

Despite the growing importance of public attention and the wide use of the concept in existing communication studies, public attention is undertheorized and inconsistently conceptualized (Webster, 2011). Many studies have treated public attention as a self-explanatory concept (see e.g., Wu & Huberman, 2007). Yet, other studies have shown inconsistencies in the conceptualization, definition, and measurement of public attention (see e.g., Camargo et al., 2018; Lörcher & Neverla, 2015; Lorenz-Spreen et al., 2019; Newig, 2004). These studies equate public attention to news attention, public opinion, or an aggregation of social media attention. This inconsistency within the literatures makes it difficult to form generalizable conclusions about what sparks and sustains public attention to an issue, generally, and within today's hybrid media system, specifically.

Furthermore, classic media theories suggest that organizational actors, particularly traditional gatekeepers, are the dominant shapers of attention since these actors control the spread of information. However, the contemporary media system challenges this assumption in three main ways. First, public attention intermixes with attention from different types of actors across different media outlets in an intertwining and interdependent fashion. Public attention evolves in a hybrid media system (Chadwick, 2017). Chadwick emphasized that the hybrid media system is "built upon interactions among older and newer media in the reflexively connected fields of social and politics" (2017, p. xi). That means, mass media and digital new media are both a part of today's hybrid media system. Actors in the system maneuver the information flows to suit their goals or influence other actors across different media. Different sets of actors are in interactive, complicated, and ever-evolving relationships (Chadwick, 2017). Unlike during the era of mass media, ordinary citizens and traditional gatekeepers coexist within today's digital media space, influencing each other in unpredictable ways. On the one hand, traditional gatekeepers maintain influence using mass media as well as by adopting media technologies and expanded into the digital space (Vaccari, Chadwick, & O'Loughlin, 2015). For example, various studies have shown that traditional gatekeepers like news and political elites use Twitter as a tool to gain public attention (Jungherr, 2014; Karpf, 2017; McGregor et al., 2017). On the other hand, ordinary citizens also influence politicians and news media by attracting attention on social media. For example, in the Black Lives Matter movement, activists generated attention among ordinary Twitter users, which, in turn, influenced news attention and elite attention to take notice of this social issue (see e.g., Freelon et al., 2017).

However, most existing empirical intermedia agenda setting studies have treated social media attention, particularly Twitter attention, as equivalent to public attention and overlooked the presence of traditional gatekeepers on Twitter (see e.g., Jones-Jang et al., 2020; Nahon et al., 2013; Su & Borah, 2019). An assumption ungirding these studies is that media platforms divide traditional gatekeepers from the general public. From a theoretical perspective, the assumption is flawed because the clear division between these two sets of actors no longer holds. Social media platforms include content from both traditional gatekeepers and everyday people. In fact, "regular people" produce highly viewed and liked content on social media. As shown in previous empirical studies, social media platforms like Twitter offer a variety of interactive paths for the transmission of public attention (Bennett et al., 2018; Segeberg & Bennett, 2011), enabling both traditional gatekeepers and ordinary people to directly influence the diffusion of attention across media outlets (Conway et al., 2015; Harder et al., 2017). Thus, findings from intermedia agenda setting studies are not enough to theorize about the diffusion of public attention within today's hybrid media system.

Second, scholars challenge the applicability of classic communication theories because ordinary people can play a critical role in effectively spreading and raising public attention to a social issue. The two-step flow theory (Katz, 1957) suggests that news media indirectly influence public attention through opinion leaders. Oliver et al.'s (1985) critical mass theory and Granovetter's (1978) threshold model both highlight the role of interdependence in information diffusion, meaning they emphasize that individuals' choice to spread information depends on how many other individuals have already spread it. Within the contemporary media environment characterized by networked communications, the interdependence between individual actors, in effect, influences the spread of attention (see e.g., Bakshy et al., 2011; Barberá et al., 2015; Foucault Welles & González-Bailón, 2020; González-Bailón et al., 2014; Piedrahita et al., 2018; Watts & Dodds, 2007). In contrast, agenda setting theory, agenda building theory, and gatekeeping theory focus on organizations' dominant role in determining public attention. Indeed, only a few agenda setting studies have considered the role of social interactions among ordinary people in the diffusion of public attention (see e.g., Erbring, Goldenberg, & Miller, 1980; Zhu et al., 1993).

Lastly, some communication researchers critique these classic theories because they do not readily account for the fluid, intertwining, and interdependent relationships between public attention and other forms of attention. In the hybrid media system, the power relation between different types of actors across media continuously changes, creating enormous flux, competition, and power (Chadwick, 2017, p. 68). Nahon's (2008) network gatekeeping theory suggests that the role of gatekeepers constantly changes between different types of actors over time because of the dynamic nature of network structures within the attention diffusion process. Simply put, network gatekeeping is a fluid and iterative mode (Meraz & Papacharissi, 2013). The interactive relationship between gatekeepers and the gated across media shift more rapidly than they did in the era of mass media (Weimann & Brosius, 2017). This process (and its speed) is amplified by the speed of information transmission on social media platforms. For example, Kwak and colleagues (2010) found that half of all the retweets a tweet garners happen within an hour of its publication. Harder et al. (2017) found that news websites and Twitter affected each other's attention in a time window of six hours. However, traditional agenda setting studies generally assume that the diffusion of attention between actors across media happens much more slowly than it does in the current hybrid media system.

Additionally, gatekeepers differ across issues and event contexts. Although scholars have theorized much less about the influence of context of this process (Nahon, 2008; Neuman, 2016), Neuman et al. (2014) found that gatekeepers varied by type of social issue. More specifically, they found that for issues or events related to security, crime, and drugs, public attention tended to *follow* news attention, but for issues or events linked to gun control, natural disasters, and

LGBT rights, public attention tended to *lead* news attention. Furthermore, Lehmann et al. (2012) found that different events sparked various patterns of Twitter attention and that these varied patterns correlated with whether mass media outlets or social interaction drove this attention. These findings demonstrate the heterogeneity of event contexts in terms of the patterns and diffusion processes of attention (Nahon, 2008), which invites the question: under what conditions do gatekeepers and the gated switch roles? In other words, when does the contemporary hybrid media system enable certain types of actors to influence public attention (Nahon, 2008; Neuman, 2016)? Given traditional media theories' "true–false dichotomous notion[s] of theory testing" (Neuman, 2016, p. 238), communication scholars have only recently attempted answering this question. Indeed, this question requires that scholars use a more dynamic model to explain the diffusion public attention within the contemporary media system.

In sum, to answer the guiding question about who shapes public attention to a social issue across media over time, the existing literature presents two key challenges. First, although public attention is an important resource in the contemporary media system, it lacks consistent conceptualization, definition, and measurement. Thus, it is difficult to tell what exactly public attention is, how to measure it, and how to theorize it. Second, in the hybrid media system, attention to a social issue spreads across media and different types of actors. With the advent of social media platforms like Twitter, public attention intermixes with attention from other types of actors (e.g., political elites, news media outlets, and advocacy groups) across media in an interactive network gatekeeping process. Consequently, it is hard to sort out the intertwining, interdependent, and ever-changing relationships between public attention and attention from other types of actors across different event contexts.

To address these challenges, this dissertation has three goals. The first goal of this work is to clarify the conceptualization and definition of public attention and to propose a robust approach to measure public attention. The second goal is to disaggregate attention from different types of social media actors (e.g., news, politicians, and individual actors). Specifically, I propose a method to typologize Twitter actors at scale to better test the influence of different types of attention on public attention. The final goal of this work is to examine patterns of public attention across different event contexts to theorize about the diffusion of public attention.

Toward theorizing about the diffusion of public attention, I focus climate change, using this current social issue as the context for analysis. Climate change is a prime context to study the dynamics of public attention and the impact of multiple sets of actors over time for several reasons. For one, climate change is a complicated and unobtrusive, topic, which most people consider distant to for their everyday lives (Djerf-Pierre & Shehata, 2017; Painter, Kristiansen, & Schäfer, 2018; Schäfer & Schlichting, 2014). As a result, this issue has received limited public attention until quite recently (Moser, 2010). Climate change also involves a wide set of actors including politicians, government organizations, news media, and various other organizations on both mass media and social media (Cody, Reagan, Mitchell, Dodds, & Danforth, 2015). Although there are multiple social media platforms, I focus on Twitter because it serves as a network stitching mechanism that connects various actors in spreading attention about climate change within and beyond the platform (Segerberg & Bennett, 2011). Also, Twitter is an increasingly vital communication tool in the mobilization and diffusion of public attention, specifically regarding climate change (Bennett & Segerberg, 2011; Kirilenko, Molodtsova, & Stepchenkova, 2015; Thorson, Edgerly, Kligler-Vilenchik, Xu, & Wang, 2016; Veltri & Atanasova, 2017a). Given that Twitter contains various types of organizational actors, I focus, in particular, on the role of news media outlets, political elites, and large advocacy groups, since Brulle et al. (2012) found that these actors had significant, long-term influence on public attention to climate change.

Computational Social Science Approach

I use a computational social science approach to understand the guiding question at the core of this study. Generally, a computational social science approach involves (a) complicated, large-size datasets; (b) real-life, digital trace data; and (c) algorithmic analytic techniques (e.g., machine learning) to apply and test communication theories (van Atteveldt & Peng, 2018). In this study, I collected digital trace data about news coverage, press releases, search queries from Google Trends, and Twitter activity to longitudinally track the dynamics of different forms of climate change attention. To identify different sets of Twitter actors, I used an automated disaggregation approach, which integrates supervised machine learning and dictionary classification. This automated method helped classify Twitter users into five categories: individual, news, political, advocacy, and other organizational actors. Then, to examine the dynamic relationships between different sets of actors and public attention, I conducted both a dynamic network analysis and a time series analysis.

A computational social science approach advances theory building and testing. The over-time digital trace data from different media platforms provide opportunities for communication scholars to track massive information flows (Neuman, 2016). This dataset also helps researchers understand the dynamics, complexities, and interdependence of networked communications in the contemporary media system (González-Bailõn, 2013). Thus, scholars can revisit classic communication theories and many of the studies published during the era of mass media (Margolin, 2019; Schroeder, 2018).

Considering the goals of this study, a computational science approach has three key strengths. First, regarding the first goal (i.e., defining and conceptualizing public attention), digital trace data allow me to longitudinally track different forms of attention (i.e., public attention, news attention, and Twitter attention) based on real-world behavior. Through empirical analyses, I measure public attention using digital trace data from Google Trends,[1] which is based on people's Google search behavior. Google Trends data have a few strengths compared to public opinion poll data. For instance, Google Trends measures public attention based on people actual search queries; it does capture people's beliefs and self-reports about their attention to particular issue areas (van Atteveldt & Peng, 2018). In contrast, polls tend shape public attention because the news media agenda often influences pollsters' choice of issues (Druckman & Leeper, 2012). Furthermore, recent studies have shown that Google Trends Index can effectively reflect public attention to climate change (Qin & Peng, 2016; Ripberger, 2011). Also, Google Trends Index is always updating (Salganik, 2017), and thus, I can analyze public attention to other forms of attention over time.

In terms of the second goal of this study, a computational science approach helps me sort out the intertwining and interdependent influence of different sets of actors over time. As mentioned earlier, the diffusion of public attention happens in an intermedia environment; yet, most existing intermedia attention studies have used aggregated Twitter attention as a proxy for public attention. In so doing, these studies created a proxy-population mismatch (Kwon et al., 2018), because Twitter is a network stitching mechanism that connects various actors actively seeking to spread climate change attention. In particular, news, political, and advocacy actors use Twitter as a tool to influence climate change attention (Brulle, Carmichael, & Jenkins, 2012).

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[1] Google Trends analyzes the popularity of Google search queries across various regions and languages.

These organizational actors also influence public attention and news attention outside of Twitter (Harder et al., 2017). Supervised machine learning helps identify different types of users among a large number of Twitter accounts.

Lastly, a computational science approach enables me to test the external validity of existing theories and hypotheses across different contexts, thereby allowing me to develop theory about the diffusion of public attention in the contemporary media environment. As mentioned earlier, communication scholars have questioned the generalizability of agenda setting, agenda building, and gatekeeping, because of the changing dynamics of the media environment. Previous studies have also found that the patterns and generation process of public attention across contexts substantially varies (Bailo & Vromen, 2017; Lehmann, Gonçalves, Ramasco, & Cattuto, 2012; Romero, Meeder, & Kleinberg, 2011; Russell Neuman et al., 2014). To examine heterogenous attention patterns and diffusion processes, computational analyses can replicate the same analysis at an aggregated-level to subpopulation-level data or apply the same analysis to different event data; doing so can reveal the potential source of difference (Margolin, 2019).

I perform a time series analysis of aggregated attention using multiple sources, including public attention, news media, and strategic organizations in general. I then replicate this analysis across multiple climate change events to examine any potential differences. I also conduct analyses at different levels of temporal aggregation, comparing the magnitude of influence at hourly versus monthly intervals. These two temporal aggregations provide two different lenses to track public attention and its relationship with other forms of attention over time. Above all, since classic communication theories are unable to fully explain the complexities of the diffusion of public attention in today's media environment, computational analyses' "abductive novelty" (Margolin, 2019, p. 6) enables me to form and test hypotheses based on real-world data.

In sum, a computational social science approach enables me to effectively track public attention based on real-world behavioral data. And, supervised machine learning helps me understand the intertwining relationship between different types of Twitter actors (i.e., ordinary individuals, news media, political elites, advocacy groups, and other organizational actors). More importantly, this abductively novel approach suggests hypotheses about the patterns and spread of public attention and, thus, enable theory building.

Structure of the Dissertation

I organized this dissertation into five remaining chapters. In Chapter Two, I discuss the conceptualization and definition of public attention found throughout the literature and explain why public attention differs from public opinion, news attention, and social media attention, highlighting its distinctive attributes—intensity, volatility, sustainability, and cyclical nature. Afterward, I review two streams of literature that explain the evolution of public attention—traditional media effect theories and information diffusion studies. On the one hand, traditional media effects theories (i.e., agenda setting, agenda building, and gatekeeping theory) assume that organizations determine public attention. On the other hand, information diffusion studies highlight the role of ordinary people in influencing public attention. Both streams of literature show the evolutions of public attention are varied in different event contexts. Upon synthesizing these two bodies of literature, I summarize the propositions as a guiding direction for the empirical studies found in Chapters 3–5. Finally, in this chapter, I briefly introduce the issue of climate change, noting how I use this social issue to narrow the scope of the dissertation in which I empirically study the patterns and diffusion of public attention in today's hybrid media system.

Chapter Three, the first empirical study, presents a trend analysis of public attention to climate change towards two primary goals. The first goal is to examine how public attention differs from public opinion, news attention, and social media attention, and the second goal is to examine how public attention correlates with other forms of attention (i.e., news attention, strategic organizational attention, social media attention) over time. Toward these ends, I first discuss existing studies about public attention to climate change. I then review literature on the role of news media, social media, and intermedia agenda setting in the generation and transmission of public attention. Next, using a Google Trends Index as a measurement of public attention, I compare public attention to public opinion (via polling data), news attention, and Twitter attention from 2011–2016 across four attributes (i.e., intensity, volatility, sustainability, and cycles). Then, I conduct Granger Causality tests with a Vector Autoregression (VAR) model to study the relationship between public attention and news attention, social media attention, and strategic organizational attention over time. Based on these analyses, I find that public attention is theoretically and empirically distinct from news attention, social media attention, and public opinion across all four attributes. Moreover, on a day-to-day level, Twitter attention tends to predict drastic but transient changes in other forms of attention, suggesting it impacts public attention to climate change in the short-term. In contrast, on at monthly level, news attention tends to predict sustained and mild changes in other forms of attention, suggesting news attention tends to influence public attention to climate change in the long-term. To study the spread of public attention across media, Twitter is an important media platform that deserves further analysis. Specifically, it is necessary to examine what actors contribute to the diffusion and the spikes of climate change attention on Twitter.

Chapter Four, the second empirical study, presents an automated method to disaggregate Twitter users—a necessary tasks to sort out the relationship between different types of actors on Twitter. Based on the findings from Chapter Three, Twitter is an important platform in the spread of public attention across different types of media. However, most existing studies about the intermedia diffusion of attention have aggregated the attention of different types of actors on Twitter and use this aggregated measure as a proxy for public attention (see e.g., Jang et al., 2017). In so doing, these studies overlook how Twitter is a network stitching mechanism (Bennett et al., 2014) connecting a wide array of actors in spreading climate change attention. Thus, to run better analyses, it is necessary to disaggregate Twitter users, making it also necessary to develop a way to topologize Twitter users at scale into distinct categories. To facilitate this categorization process, I use an automated method that disaggregated Twitter users from four climate change related events into five mutually exclusive categories: news actors, politicians, advocacy organizations, and other organizational actors.

I also tested and validated the accuracy of this automated method, finding that it effectively classified Twitters users from these four climate change-related events into their correct respective actor categories. Furthermore, a quick review of Twitter users across these events reveals that Twitter is a hybrid ecology, which involves various organizational and individual actors, such as large international non-governmental organizations, diplomats, to climate change advocates, and climate change doubters. The large mix of actors represented in these different events demonstrates the need to disaggregate Twitter users when attempting to understand the intermedia diffusion of attention, particularly when considering the issue of climate change.

Chapter Five, the third and final empirical study, is about the intermedia diffusion of climate change attention during different events. Different actors across media influence public attention, but it is challenging to parse out the intertwining, interdependent, and ever-changing relationship between and among actors across different types of media. Toward understanding these complex relationships, I first briefly recap some of the literature discussed in depth in Chapter Three and Chapter Four and then address a major limitation of found in both intermedia agenda setting studies and information diffusion studies. Then, I discuss the importance of studying and theorizing the changing relationships between actors across media in different contexts. Afterward, I discuss the findings of my dynamic network analysis and time series analysis, which I conducted to examine the spread of climate change attention within and beyond Twitter.

The findings of these analyses contribute to the existing literature in two ways. First, the diverse attention patterns and the changing relations between actor types across media in these distinct events invites new theoretical opportunities to understand the contemporary diffusion of attention. Second, this work provides evidence of the importance of considering the context in which events take place as well as the dynamism of the gatekeeper role in the study of attention diffusion within and beyond Twitter.

In Chapter Six—the final chapter—I summarize the findings of each chapter and return to the main question about what shapes the dynamics of public attention to a social issue across media over time. Furthermore, I discuss the contributions of this research to the continued theorization of public attention, as well as the contributions of computational social science methods to the public attention literature. Ultimately, I conclude with opportunities for future research.

CHAPTER 2: PUBLIC ATTENTION IN THE HYBRID MEDIA SYSTEM: CONCEPTUALIZATION AND CAUSES

In today's media environment, the mass influx of media content and the proliferation communication technologies create an imbalance between the demand and supply of public attention. As a result, people tend to shift their attention quickly between topics, adding uncertainty and complexity to our understanding of the causes of public attention. First, only a few social issues receive substantial public attention at any given time, while others are short-lived, spiking people's attention and then, soon afterward, falling into oblivion (Castillo, El-Haddad, Pfeffer, & Stempeck, 2014; García-Gavilanes, Mollgaard, Tsvetkova, & Yasseri, 2017; Romero et al., 2011). But scholars are unsure of what kinds of issues are lasting, garnering prolonged public attention (González-Bailón, 2018). Second, our media environment adds complexity to explanations about what causes changes in public attention. Specifically, what actors and communication behaviors generate and spread public attention to different social issues/events across different media platforms? Traditional media effects theories such as agenda setting, agenda building and gatekeeping emphasized the role of organizations and elites, such as journalists and politicians. And yet, studies of information diffusion in computer and information science have increasingly found that ordinary people play a prominent role in influencing public attention. The changing media landscape has perhaps limited the explanatory power of traditional media theories. As a result, communication scholars need to rethink theories of public attention (Neuman, 2016).

In addition, although many studies focus on public attention in today's new media environment, a consistent conceptualization of public attention is missing. Many studies treat public attention as a self-explanatory concept (e.g., Camargo et al., 2018; Lehmann et al., 2012).

Meanwhile, others equate it with public opinion, policy attention, or media attention (e.g., Henry & Gordon, 2001; Newig, 2004; Zhu, 1992), even though these constructs are markedly different from one another, as I show in this dissertation (Newig, 2004). Each form of attention has distinctive patterns as it relates to a social issue/event over time. Further, news media attention, public attention, and attention from political elites also influence each other, forming a symbiotic relation over time (Conway et al., 2015; Jang et al., 2017; Russell Neuman et al., 2014; Su & Borah, 2019b). Thus, the inconsistent conceptualization and measurement of public attention, and the findings from existing empirical research on public attention could add difficulties to form generalizable conclusions about public attention. Accordingly, there is substantial work needed on theorizing public attention, its causes, and its temporal attributes.

In this chapter, I review the existing literature on public attention, highlighting the diverse ways scholars theorize and define this concept. Based on this review, I then propose a conceptualization of public attention as a resource that creates economic, political, and social value in the hybrid media system (Chadwick, 2017). In a hybrid media system, mass media and digital media co-exist and mutually influence each other through content produced via both older and newer media logics. The system connects organizational and individual actors who are adaptive and interdependent on each other in complex and frequently changing dynamics (Chadwick, 2017). Next, I review two main bodies of literature that explain the cyclical nature of public attention. I first consider literature focused on agenda-setting and agenda-building mechanisms that generate public attention. Next, I review literatures on social movements and information diffusion that use network mechanisms to explain patterns in public attention over time. Informed by these bodies of scholarship, I propose a series of propositions and one guiding research question of this study. Finally, to set up this study, I conclude this chapter by introducing the issue of climate change, which I use as the research context for this study.

The Conceptualization of Public Attention

Although scholars across research areas agree that public attention is a vital construct in today's changing media environment (Newman, 2016, p.206; Schroeder, 2018, p.16), they inconsistently conceptualize public attention and use a plethora of terms for the concept. For example, in agenda-setting studies, scholars often use public attention interchangeably with these terms: public opinion, public agenda, or issue attention (e.g., Edy & Meirick, 2018). In audience analysis studies, scholars sometimes refer to it as aggregated audience attention (e.g., Webster & Ksiazek, 2012). In early agenda-building studies, researchers often equate public attention with news attention (e.g., Newig, 2004) or policy attention (e.g., Erbring et al., 1980). And, in the more recent studies on the dynamics of public attention online, scholars often treat the concept as self-explanatory and refer to it interchangeably with collective attention (e.g., Wu & Huberman, 2007). Problematically, these studies assume that these varied constructs are the same as public attention, with equivalent definitions and attributes. However, these concepts, while similar and related, are not the same. Rather, these various concepts have different definitions, implications, and temporal patterns, as I illustrate below and throughout the empirical analyses in upcoming chapters. Specifically, I discuss the differences between public attention and public opinion, news attention, policy attention, and social media attention. By clearly differentiating these terms, I provide the necessary grounding to later propose a novel measurement strategy for public attention in Chapter 3.

Public Attention as Public Opinion

As mentioned, scholars often use the terms public attention and public opinion as if they are the same. While they may be closely related concepts, there are few key distinctions between them.

First, public opinion and public attention are different in their definitions. Public opinion is the aggregation of individual attitudes toward an issue (Druckman & Leeper, 2012), as the construct, “opinion,” denotes individuals’ value judgments. More precisely, opinion refers to a “consistently favorable or unfavorable manner with respect to a given subject” (Fishbein & Ajzen 1975, p. 6). Since researchers generally measure public opinion using poll questions such as, “what is the most important problem to the country?” it is also a judgment on the relative importance of an issue by comparing it with other issues (Rogers & Dearing, 1988). Thus, public opinion implies a prioritization of different issues.

In contrast, the construct “attention” is neutral and reflects the time or energy that an individual spends on an issue. As opposed to “opinion,” the amount of time someone spends understanding an issue carries neither a positive nor a negative bent. Public attention also does not suggest the actual importance of issues. Indeed, an alarming issue may garner little public attention (Downs, 1972). Downs pointed out that the environmental issue is an example of this phenomenon. Although the quality of our environment has always been a severe issue, the public have not paid enough attention to it for a long time (1972). It is also impossible to examine public attention based on the ranked importance of all the issues because countless issues saturate the media environment and compete for the public’s limited attention.

Second, public attention and public opinion are different in temporal dynamics. Newig (2004) pointed out that public opinion is less likely to be quickly changed than public attention because it takes a long time to redirect individuals' attitudes about an issue. Similarly, Druckman and Leeper (2012) consider public opinion less volatile than what opinion polls reflect because polling questions are highly contingent on changing media coverage. They also argued that public opinion on an issue tends to stay stable, especially if individuals' opinion on the issue is strong and there are relatively few competing arguments (Druckman & Leeper, 2012). In an experimental study about the stability of individual opinion, Chong and Druckman (2010) found that public opinion remained unchanged for many well-developed issue areas, including the Patriot Act, urban sprawl, healthcare, and new scientific technologies. Furthermore, individuals' opinions about these key issues remained stable even when researchers exposed them to various conflicting messages.

In contrast to public opinion, public attention is more variable, and changes more frequently in response to vast array of stimuli involved in real-life (Hasan & Schwitter, 2018; Lin, Keegan, Margolin, & Lazer, 2014). For example, King et al. (2013) found that 50c party posts, nationalist propaganda, distracted public attention on social media away from some critical social issues in China. Overall, public attention is "dynamic, episodic, and ephemeral" (Ripberger, 2011, p254) but public opinion is stable and unlikely to change quickly (Newig, 2004).

Public Attention as News Attention or Policy Attention

Studies often use news or media attention (e.g., Newig, 2004) as a proxy for public attention. In other words, scholars often consider public attention a mirror image of media attention, assuming that the intensity of public attention about a specific issue matches the frequency of news media's coverage of said issue (Erbring et al., 1980). However, numerous studies have shown that mass media attention often does not perfectly align with public attention

(Conway et al., 2015; Neuman, 1990; Russell Neuman et al., 2014; Su & Borah, 2019). For example, Neuman (1990) examined the relationship between the volume of news coverage and the corresponding public attention about issues such as poverty, racial problem from 1945 to 1980. He found that once the news coverage of an issue reaches a certain threshold, public attention will not grow in tandem. In today's media environment, news media no longer monopolizes public attention (Tufekci, 2013). Now, digital media offers people more choices and endless sources of online information. Kwak et al., (2018) found that public attention, measured by Google Trends Index, ignored mainstream news media outlets in some countries, measuring instead users use of online news' resources. A recent published study by Pew Research found that more than half of adults in the United States often or sometimes obtain their news from social media platforms (Pew Research, 2019). News media attention also does not correspond with social media attention. For example, Edgerly et al. (2018) found that the extent of newspaper and television coverage of the 2016 U.S. presidential primaries did not reflect the volume of news stories about the primaries shared on Facebook during the same period.

Other studies treat public attention as equivalent to policy attention. Erbring et al.(1980) define policy attention as the general public's concerns. These studies conceptualize public attention as attention from public spheres or the public arena. Both are a virtual place that gathers ordinary people and a constellation of organizational actors to collectively define a social issue (Hilgartner & Bosk, 1988). This strand of scholarship conceptualizes public attention as an assemblage of attention from the public and different sets of actors, including the government and news media. This conceptualization, however, may conflate or erroneously aggregate public attention with policy attention. In so doing, this understanding overlooks the dynamic relationship between these two related, but distinct, constructs.

Public Attention as Collective Attention on Social Media

Given the wide presence of everyday people on social media platforms like Twitter, many studies, particularly ones focused on intermedia agenda-setting (e.g., Jones-Jang, Hart, Feldman, & Moon, 2020), treat social media attention as public attention. Similarly, several studies from information science focused on the spread of attention also treat public attention as synonymous with collective attention and do not provide an explicit definition for public attention" (e.g., Lorenz-Spreen et al., 2019; Sasahara et al., 2013; Wu et al., 2011). Again, this conflation of terms is problematic. First, Twitter users are not representative of the general population. According to a recent Pew research study, Twitter users are more educated, younger, and more likely to be Democrats than the general public in the United States.[2] The patterns of what receives attention on social media are also sometimes different than the patterns of issue attention found in surveys of the general public. For example, Twitter may reflect more attention towards political issues than other social media platforms, since the most active Twitter users are more likely than other users to tweet about political issues. Second, social media encompasses both individual users and other entities. For instance, based on a random selection of 20,000 active users from Twitter, McCorriston et al., (2015) found around 9.6% of them were organizational accounts, and that these organizational accounts were more highly connected than individual users. Organizational accounts showed different messaging behavior patterns than individual users (Kwon et al., 2018). As such, it is problematic to use collective attention on social media as a proxy of public attention.

[2] https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/

Public Attention as a Resource in the Hybrid Media System

The generation and distribution of public attention increasingly take place in the context of a hybrid media system, which Chadwick (2017) describes as the interaction between old media logics and new media logics, where logics represent "bundles of technologies, genres, norms, behavior and organizational forms" (Chadwick, 2017, p. 109). In a hybrid media system, traditional media and social media coexist, compete, and adapt with each other. In this context, non-news media organizations, including politicians, elites, for-profits, and nonprofits, directly reach the general public via social media, thereby enhancing their direct influence on public attention. Social media also gives voice to ordinary people and grassroots groups, enabling them to likewise vie for public attention in pursuit of their political goals, values, and interests (Chadwick, 2017). The power dynamics among different actors are adaptive, intertwined, and constantly in flux, and these fluid dynamics shape the cycles of political information over time (Chadwick, 2017).

Considering the characteristics of the hybrid media system, for the purposes of this study, I define public attention as the attention of ordinary people—those who do not represent a particular organization, such as news media, political parties, lobbies, or major advocacy groups. More specifically, I define public attention as the shared awareness expressed by a collection of ordinary people on any given issue. Furthermore, I conceptualize it as a scarce and valuable resource in a hybrid media system for two reasons. First, from the perspective of the attention economy, public attention is valuable because of the imbalance of its supply and demand in today's media environment (Webster, 2011). The supply of public attention is limited. It is unfolding like a zero-sum game in which increased attention to one issue means the loss of attention to another issue (Hilgartner & Bosk, 1988b; Neuman, 1990; Zhu, 1992). The fragmentation of audience across different media outlets further limits the supply of public attention (Fletcher & Nielsen, 2017; Webster & Ksiazek, 2012). On the other hand, the demand for public attention is ever-growing, with the saturation of media contents alongside the proliferation of communication technologies. Politicians, news media, activists, and advertisers all need massive amounts of attention as a currency to achieve economic, social, or political value (Webster & Ksiazek, 2012). As a result, different sets of actors compete with each other to maneuver public attention across media. For example, social movement studies emphasize collective attention as a valuable resource in the success of a movement, particularly with the rise of social media (e.g. Thorson et al., 2016; Thorson & Wang, 2019; Tufekci, 2013). Mobilizing the public and creating spikes of public attention on social media can further amplify the impact of the movement by attracting news attention and elite attention (Freelon et al., 2018).

Because of intensive competition between different sets of actors for public attention, it is necessary to differentiate public attention from other related constructs, because doing so helps understand the actual attributes and causes of public attention. Despite the widely understood value of public attention, few studies treat it as an independent analytic category (Tufekci, 2013). In the mass media era, gaining public attention at scale meant gaining attention from news and civic media, but in today's media environment, the relationship between public attention and other sources of attention is more complicated. Both individuals and organizations use digital media to shape and reshape online public attention. Public attention could both be a posterior effect and an a priori cause of other sources of attention (Tufekci, 2013). For example, Wells and colleagues (2016) aggregated a swath of data related to Trump's presidency, such as the scheduling of Republican debates and Trump's personal tweets. Through a time series analysis of this data, they found that Trump's strategic Twitter curation and his impact on the partisan media outlet, Breitbart, quickly gained him public attention, which he, in turn, successfully leveraged into the mainstream media agenda (Wells et al., 2016). As evidenced by this example, it is necessary to distinguish public attention from other sources of media attention to understand how the latter participates in the production and distribution of the former.

Four Attributes of Public Attention

Based on my synthesis of existing literature on public attention in the hybrid media system, public opinion, and collective attention on social media, I theorize four attributes of public attention: intensity, volatility, sustainability, and cycles. The empirical analysis chapters to follow examine these attributes as they characterize public attention and contrast them with the characteristics of other forms of media attention. To set up these analyses, I first describe each of these attributes in more detail.

Intensity refers to the strength of public attention when it reaches its peak. For example, intensity captures the volume of tweets from ordinary people at their highest peak. Typically, in a media outlet, a growing influx of content on a specific issue corresponds with rapid growth in its public attention. However the inverse also holds, meaning the increasing decline of content of a specific issue often also correlates with declining public attention value (Gomez-Rodriguez, Leskovec, & Krause, 2010; Lorenz-Spreen et al., 2019). But, as mentioned before, only a few issues generate intense public attention (Barabási, 2005), and it is unclear which issues induce more intense public attention than others.

Sustainability refers to how long public attention on a specific issue can last. Generally, public attention on any issue is short-lived and rarely endures over time. The intensity of public attention wanes over time. For instance, very few issues sustain public attention over a protracted time period. But far fewer issues retain their intensity over long stretches of time, too. Empirical studies suggest characteristics of issues or events might affect the sustainability of attention. On one hand, people's attention to unexpected events is less sustainable. Castillo et al., (2012) found that news media may induce an acute spike in online public attention after unexpected events (e.g., a natural disaster), but after the event, this attention quickly wanes. On the other hand, people's attention are more sustainbale to the events/issues with high initial atteniton than those with low intial atteniton. Geiß (2019) found that news attention can hardly raise more public atteniton if the baseline of public atteniton to an issue is already high. That means, public attention becomes self-sustaining when the level of its baseline attention is already high enough.

Public attention also has high *volatility*, meaning people quickly shift their attention from one issue to another. Indeed, attention volatility may be increasing over time. Using longitudinal digital trace data from Google, Twitter, Reddit and movie ticket sales, Lorenz-Spreen et al. (2019) found that public attention increasingly switched from one social issue to another from 2013–2016. Furthermore, they found that the volatility of public attention on specific issue is positively correlated with the volume of media content on the issue. In another study about the diffusion of memes on Twitter, Weng et al. (2012) found that as competition over attention increases, the volatility of people's attention to a particular meme also increased. These findings suggest that public attention operates as a "zero-sum game" (Zhu, 1992); increasing attention to an issue comes at the cost of attention to another issue.

Public attention also changes in *cycles*. Downs' (1973) suggests the development of public attention cycles through five key stages: (a) the pre-problem stage, where objective conditions of the issue are far worse than when the public became interested in it; (b) the stage of alarmed discovery and euphoric enthusiasm, where the public is suddenly alarmed by the issue and pays more attention to solving problem; (c) the stage where the public realizes that the costs of the solutions are too high; (d) the stage where public interest declines as members become discouraged or bored by the issue; and (e) the post-problem stage, where another issue replacing the initial issue, thereby restarting the cycle all over again. But many scholars criticized the generalizability of linear sequential stage of issue development. For example, Henry and Gordon (2001) criticized this model for its inability to describe when precisely public attention spikes and plateaus. Additionally, others rightfully point out that public attention varies by people's health (Shih, Wijaya, & Brossard, 2008), cultures (Brossard et al., 2009), and between their engagement with traditional media versus digital media (Lörcher & Neverla, 2015), meaning it is unclear if the cyclical changes of public attention actually reflect or depend on the different stages of issue development.

What Causes Public Attention?

What causes public attention in the contemporary hybrid media environment is a challenging question; however, two streams of existing literature suggest different explanations for its generation and transmission. The first set of literature proposes that organizational actors, primarily elite politicians and news media, determine the foci of public attention. Although public attention also forms a feedback loop that influences attention from traditional gatekeepers, the literature downplays this connection. In this body of literature, digital media maintains or expands the power of traditional gatekeepers have in determining the flow of public attention. Theories such as Downs' issue attention cycle, public agenda-setting (McCombs & Shaw, 1972), public agenda building(cite), and gatekeeping (Sheomaker, 1991) fall within this subset of literature. I discuss these theories more below.

The second set of literature focuses on online networks of communication related to the sharp increase or spikes in public attention and the diffusion of attention. For example, some studies have found that particular network mechanisms, such as the degrees[3] of the actors, the strength of network ties, and homophily in communication networks, are related to attention diffusion (e.g., Bakshy et al., 2011; Weng et al., 2012; Wu et al., 2011). Furthermore, these studies suggest that ordinary people play an important role in directing spikes in public attention. In particular, several studies on major contemporary social movements, such as the Occupy Movement, the Indignados Movement, and Arab Spring, have found that people's perceptions of changes in public attention seem to drive information flow across online communication networks (Barberá et al., 2015; González-Bailõn, 2013; González-Bailón et al., 2011). Within the context of online communication networks, these studies show that ordinary people can generate substantial attention on a social issue through informal peer-to-peer communication. Emerging concepts and theoretical frameworks, such as curated flows (Thorson & Wells, 2016) and network gatekeeping (Barzilai-Nahon, 2008), adapt and extend beyond traditional media theories, and in so doing, they help explain changes in public attention within today's hybrid media system. At the same time, however, these studies and theories do not come without their own assumptions and limitations. To follow, I analyze these two sets of literature and discuss their respective limitations.

Issue Attention Cycle

Downs's (1972) issue-attention cycle is one of the earliest theoretical models that explains the rise and fall of public attention to social issues. Scholars widely apply his five-stage issue attention cycle to their work (see e.g., Schäfer, Ivanova, & Schmidt, 2014), but few pay close attention to his propositions about what moves public attention forward and backward

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[3] In social network analysis, a node is an actor (could be people or organizations) in the network. The degree is the number of total connections that the node has with others.

through these stages. His propositions present two key takeaways. First, news media plays a vital role in influencing how the public understands an issue, thereby pushing public attention from one stage to another. Following a five-step cyclical process, Downs argued that the issue attention stage depends on how the public understands the costs and benefits of addressing said issue. An issue tends to receive less and more fleeting attention if: (a) solving it benefits only a small part of the population, (b) the cost of solving it is high, and (c) it is not dramatic or entertaining to most people. Public understanding of the costs and benefits is contingent on how news media interpret the issue to the public. Second, according to Downs, moving public attention across each stage requires a complicated interaction among media, government, and public attention. In general, both news media and government attention influence public attention with feedback loops between each other. As media influences public attention on an issue, public attention, at the same time, guides news attention. However, when news media overreports on an issue, the public tends to lose interest. As for the relationship between government attention and public attention, public attention pressures politicians to solve the issue at hand and, thus, "orients" government attention. Although the public can pressure the government to take notice of particular issue, the government can also suppress public attention by informing the public about the costs associated with solving the issue, as suggested or, at times, demanded by the public.

Agenda Setting and Building

Many media scholars apply Downs' issue attention cycle, but they often simplify his explanations about public attention by only or over emphasizing the role of news media. More precisely, this stream of studies takes a media-centric approach and suggests that the news media sets the public agenda by influencing the salience of an issue (McCombs & Shaw, 1972; 1993) and building consensus amongst the public on what constitutes the important issues of the moment (Lippmann, 1949; McCombs, 1997; McCombs, 2004). Cohen's agenda setting theory argues that news media is "stunningly successful in telling its readers what to think about" ((E. M. Rogers, Dearing, & Bregman, 1993), p. 72). On other hand, agenda building scholars in communication seek to understand who sets media attention (E. Rogers & Dearing, 1988)These studies are organizationally oriented and focus on how organizations, such as public relations firms, influence media attention (Yang & Saffer, 2018). Like McCombs and Shaw's agenda setting theory, Shoemaker's (1991) gatekeeping model positions mass media as gatekeepers that decide which issues receive public attention. In fact, information often must pass through several such gatekeepers before successfully gaining public attention (Shoemaker et al., 2009).

Media scholars have also found strong intermedia agenda setting effects, which transfer the saliency of an issue from one media outlet (e.g., Twitter, Facebook, and traditional media) or from certain types of media (e.g., partisan media and elite media) to another outlet (Jang et al., 2017; Meraz, 2009). For instance, Lim (2006) discovered that issues (or the media agenda) moves from elite, traditional mass media outlets to less-elite ones, such as from newspaper to TV or from newspaper to wire service (2006). Even considering the growing presence of digital media, traditional media are still powerful forces in directing public attention. Yu and Aikat (2006) found that media agendas are convergent between portal news and traditional legacy media in television and newspapers.

Digital media enable organizational actors to directly communicate with the public and shape their attention. Even so, empirical findings suggest that traditional gatekeepers, such as news media, political elite and large organizations, still frequently dominate the shape of public attention on digital media outlets. For example, small advocacy organizations still actively compete with large international NGOs such as Oxfam to gain attention from mainstream news media as a way to gain large-scale public attention on important social issues (Thrall, Stecula, & Sweet, 2014b). Communication scholars likewise embrace the role of digital media in agenda setting. For example, Shaw and McCombs (2008) include social and interpersonal media (horizontal media) as an extension to mass media (vertical media) in the agenda setting process. Likewise, in building agenda setting theory, Vargo and Guo (2017) proposed the network agenda setting model, which considers how often multiple issues are salient within the news at the same time. They also expanded the model to explain issue attention transfer between social media and mass media, as well as from news media to the public agenda (Vargo, Guo, & Amazeen, 2018). Additionally, Ognyanova (2020) proposed a dynamic and multidimensional network model of agenda setting that embeds audience, information sources, and issues. This model integrates network mechanisms, media, intermedia, and interpersonal influence in agenda setting theory.

Although these recent adaptions of more traditional agenda setting models provide more nuance and help better illuminate drivers of public attention and agendas, these models have a few key shortcomings. They rely on several assumptions that limit their generalizability in explaining public attention in hybrid media system.

First, this work emphasizes the role of organizational actors, such as news media, politicians, elites, and advocacy groups, in shaping the public attention. While these theories concede that the general public informs this process, they still assume that organizational actors are the main initiators of public attention and that the general public mostly just respond to what organizations signal is important. However, with social media, ordinary people can bring awareness and attention to a particular issue through informal, peer-to-peer communication, which, in turn, can influence traditional gatekeepers. For example, research on social movements, in particular, documents how everyday social media users influence news media, elites, and politicians' attention. During the 2011 Egyptian uprising, ordinary users on various social medial platforms became prominent figures, who helped shape the narrative of the movement. These users also elevated others to elite status through networked gatekeeping, and they interacted with elites in a fluid and iterative ways, effectively revising, rearticulating, and dispersing of the narrative about the uprising (Meraz & Papacharissi, 2013). In another study, Freelon and colleagues (2018) tracked Twitter data about the Black Lives Matter movement, finding that activists coordinated social media messaging to attract news media and, thus, gain the attention of the political elites. These studies have shown that by using digital media, the general public has increased its power in agenda setting, influencing the flow of information, and expanding public attention. Yet, these organizational-centric studies downplay the key role general users serve in these processes.

Another limitation of this work, particularly in intermedia agenda setting, is its operationalization of public attention social media attention (e.g., Twitter attention). The assumption is that media platforms divide the traditional gatekeepers and the public. As mentioned before, organizations also use social media to directly communicate with the public. For example, news organizations publish news on social media to engage larger audiences (Welbers, Van Atteveldt, Kleinnijenhuis, Ruigrok, & Schaper, 2016). Journalists also use social media to construct narratives and comment on, for example, political happenings during presidential elections (Mourão, 2015). In addition to news actors, politicians (Kreiss, 2016) and nonprofits (Lovejoy & Saxton, 2012; Yang & Saffer, 2018) alike expanded their presence on social media as a way for them to create news and public attention for their specific objectives. For example, politicians use social media to manipulate public attention in political campaigns

(Kreiss, 2016), elections (Jungherr, 2014b; Wells et al., 2016), and debates (Freelon & Karpf, 2015). More specifically, during election season, politicians publish campaign-driven content on Twitter and engage with journalists as part of "news management" (Nuernberg & Conard, 2016). These findings show the presence of traditional gatekeepers and the interactive and symbiotic relationship between them and the ordinary people on Twitter. Therefore, the treating social media as equivalent to public attention overlooks these interactive communications and their potential influence on public attention.

A third challenge of this literature is the time compression of media effects. Agenda setting and agenda building theories stemmed most directly from Bernard Cohen in 1963 (Rogers & Dearing, 1988)—the theories were developed in a much slower paced media environment than today. Initially developed more than 50 years ago, these theories generally assume it takes a longer time than today for the public to absorb the mass media and understand the importance of an issue (Weimann & Brosius, 2017a). As shown in agenda setting studies within the context of mass media, it takes approximately 4–8 weeks for the news media agenda to affect the public agenda (McCombs, 2004), but this may not be the case in today's media environment. With the advent of social media, users can affect the agenda almost in real-time. As Chadwick (2017) pointed out, the communication and the power relations between actors in the hybrid media environment are constantly changing. The temporal interrelation between different media outlets could happen within a day (Wells et al., 2019). Considering newspaper, television, radio, news websites, and Twitter in the Belgian 2014 election campaign, Harder et al. (2017) found that websites and Twitter quickly set the public agenda within a day.

The diffusion of attention on social media sometimes travels at viral speeds, reaching large groups of people in a matter of minutes or a few short hours (Nahon, 2013). Examining 106 million tweets, Kwak et al. (2010) found that half of retweets occurred within 1 hour of the initial tweet and 75% of retweets happened within the first day. As for Facebook, Bakshy et al. (2012) conducted a field experiment in which they observed the sharing behavior of 253 million users and found that the, on average, people reshared a friend's post within six hours of its publication. The lifespan of content on social media is also short. For example, on Twitter, a hashtag stayed within the top 50 list for only 11.9 hours in 2016 (Lorenz-Spreen et al., 2019). As many agenda setting studies use weekly, quarterly, or monthly time scales for analyzing public attention, this aggregated time compression overlooks the temporal impact of each sources of attention and overestimate the influence of news media, although the timings of these different retweets, reshares, posts, etc. may contribute to spikes in public attention.

Given these three main limitations of organization-centric studies on public attention, a few scholars have shifted the conceptualization of agenda setting toward a process of agenda diffusion, agenda sharing, or information flow. Weimann and Brosius (2017) reviewed how agenda-setting studies evolved with the rise of the digital media. Based on their review, they suggested that it is more accurate to reframe agenda setting as agenda diffusion, because the concept of "diffusion" better reflects the interactive, multi-step flow of communication, and the social networks in which these flows are embedded. What's more, Weimann and Brosius explained that digital platforms accelerate the process of agenda diffusion, as well as that the whole process of agenda diffusion is more complicated than suggested by existing agenda setting and building theories. Furthermore, their work mirrors the way some agenda setting studies have reframed their focus. For instance, Jang and colleagues (2019) adopted approaches typical of intermedia agenda setting studies by analyzing the temporal correlations between Twitter, news media, and Reddit posts about vaccines. Using this temporal approach, they framed their research as an examination of the information flow and agenda diffusion across media outlets. This shifting understanding of agenda setting and building suggests that research on public attention should reconsider what the changing media environment means to the evolution of public attention. A more relevant question worth pursuing is, what drives the dramatic increase of public attention in the contemporary hybrid media environment, saturated by so many choices and changing rapidly (Edy & Meirick, 2018). How public attention evolves in the complex dynamics between the different sets of actors in the contemporary mediascape is a central challenge for studies of public attention (Neuman, 2016).

Online Information Diffusion and Network Mechanisms

Although agenda-setting scholars have only just begun to introduce the "diffusion" concept to the study of public attention, information diffusion studies—the second stream of theories and studies discussed—have widely adopted this approach to explain spikes in public attention. Particularly in online social movement studies as mentioned before, the success of social movements relies on whether they can generate a huge amount of public attention. Social movement studies about the diffusion of public attention suggest that spikes of public attention are a result of more complicated network mechanisms. This stream of research perceived information diffusion as a social process. The network influences the process by interdependence among ordinary people, which is the most basic network mechanism (González-Bailón, 2017). Ordinary people as crucial actors in spreading attention about a given issue through social networks. For example, based on a complex network analysis of 622 million tweets over the span of a year, Goel and colleagues (2016) found that most viral posts only spread within close ties via just a few steps. More specifically, they found that viral diffusion rarely happened by a broadcast model, where only a few extremely influential broadcasters dominated the diffusion.

Instead, viral diffusion happened most often when both ordinary people and large broadcasters collaboratively contributed to is diffusion. In fact, ordinary users with average or below average influence tend to be the most influential actors in viral diffusion (Bakshy, Hofman, et al., 2011).

This literature also addresses the symbiotic and dynamic relationship between public attention and traditional gatekeepers. For example, Lotan and colleagues (2011) examined tweets during the Tunisian and Egyptian uprisings and found that the relationship between media outlets and individual users was symbiotic. That is, in the networked production and dissemination of news on Twitter, actors, including journalists, bloggers, and activists, retweeted one another, thereby encouraging their audiences to tweet more and, ultimately, increasing public attention.

Two types of ordinary people embedded in the communication networks are important for understanding attention diffusion through social networks: opinion leaders and the critical mass. Opinion leaders are ordinary users who have gained trust and the power of influence through interpersonal communication, and thus, these leaders can directly influence public attention (Cha et al., 2010; Kirilenko & Stepchenkova, 2014; Wu et al., 2011). Katz (1957) theorized this mechanism as a two-step mediated process, where opinion leaders, who were more exposed to mass media, mediate its influence on ordinary people. Opinion leaders generate public attention by an emerging mechanism, which Tufekci (2013) termed "networked microcelebrity activism"—a process by which microcelebrities use social media to engage with ordinary people, share politics views, and generate attention for their causes. In short, microcelebrities are "non-institutional actors" whose power comes from informal daily communication through "a combination of testimony, advocacy and citizen journalism" (Tufekci, 2013, p 850). For example, considering the ongoing climate change debate, Kirilenko and Stepchenkova (2014) examined a year's worth of data from Twitter on climate change and found that opinion leaders influenced public attention and discourse about climate change. And so, while traditional media initiate of the majority information online, opinion leaders help spread the news (Kirilenko & Stepchenkova, 2014). Illustrating this point, Wu et al., (2011) observed 42 million Twitter users and 1.5 billion tweets. They found although many retweets originated from a minority of elite users, the information reached the audience on Twitter via a large group of intermediaries.

Critical mass refers to large clusters of ordinary users who are easily influenced or susceptible to opinion leaders. More than the opinion leaders, Watts and Dodds (2007) found that the susceptibility of the neighboring peers is equally important in driving information diffusion. Through computer simulations of social networks, they showed that in most conditions, a critical mass of easily influenced people drove a large cascade of influence, although opinion leaders initiate the information. In another study, tracking tweets about the Indignados Protest in Spain, González-Bailón et al. (2013) identified a group of ordinary users as “hidden influentials.” Although at the periphery of online communication networks, these hidden influentials were central in Twitter networks focused on the protest. Specifically, these hidden users gave the movement an identity and frame, which influential, and often elite, users later projected. The study showed that a critical mass is equally important as opinion leaders, because the impact of opinion leaders becomes limited without their attention and efforts in mobilizing other ordinary users.

These empirical findings have driven new concepts and theoretical frameworks, which have renewed traditional media theories. For example, Nahon’s (2009) networked gatekeeping theory proposes that gatekeepers are not a fixed set of elites, but sometimes include ordinary people. Networked gatekeepers control the information in and across communication networks.

The process of networked gatekeeping is dynamic, as the interest and goals of the stakeholders constantly change. As such, those who were once gated can potentially become gatekeepers; therefore, the composition of gatekeepers is fluid, changing over time. Separately, Thorson and Wells (2016) proposed curated flows as a framework, arguing that in today's media landscape, the processes of media content curation involve not only traditional newsmakers, but also individual media users, social contacts, advertisers, and computer algorithms. They recommended that in order to understand the media exposure and effects in today's media ecology, communication scholars should dedicate more work to "detecting the competition, intersection, and overlap of these flows" (Thorson & Wells, 2016, p 309). The ideas such as networked gatekeeping and curated flows are promising developments, as they consider the dynamic interactions among media platforms, social institutions, ordinary users, and communication networks that collectively filter and curate information flows (Bennett & Pfetsch, 2018).

Admittedly, this set of studies sheds light on ordinary people's newfound ability to directly influence organizational attention and expand the intensity of public attention, given the advent of digital media, particularly social media platforms. Despite these gains, however, ordinary people's power to influence public attention is still limited. First, most research focuses on digital media or social media to study information diffusion networks, but in real life, the boundary between digital media and mass media is blurred. For example, publics still actively watch television, even though digital media is becoming increasingly mainstream (Chadwick, 2017). Freelon and Karpf (2015) studied the interactivity between Twitter and TV during the 2012 U.S. presidential debates, finding that ordinary users often "dual-screened" the event; that is, they watched television coverage of the debates while, at the same time, commenting on their social media feeds and reading others posts about the debate too. In a separate study about the 2013 Italian presidential campaign, Marchetti and Ceccobelli (2016) conducted a qualitative assessment and found that during the electoral period, print media and television covered political hashtags on Twitter, but most of the time, they influenced the trending topics on Twitter. However, the network models from the information diffusion studies are still limited to account for the potential influence from the mass media outlets that is outside Twitter (Lazar, 2020).

Second, this set of studies may have downplayed the role of traditional gatekeepers, as some of them, for example, the legacy news media outlets, still dominate content production and distribution (Hindman, 2018) and, thus, are still the main sources of information on the web (Mukerjee, Majó-Vázquez, & González-Bailón, 2018). Meanwhile, most of the content circulating on social media derives from mainstream media content. Using millions of tweets, Wu and colleagues (2011) found that 20,000 users are responsible for 50% of all retweeted URLs in their sample, and organizational users, such as news media outlets, posted the majority of those tweets.

Public Attention and Event Contexts

The studies I have reviewed so far have shown that what shapes public attention is far more complicated than Downs' (1972) issue attention cycle would suggest and often beyond the explanation of the current communication theories, which originated in the mass media era. In addition, a few empirical studies in both agenda setting and information diffusion have demonstrated another layer of complexities and uncertainty about public attention. These studies have shown that the patterns and triggers of public attention are different across event contexts, as I describe below.

In terms of what explains public attention, agenda setting scholars have shown that the size of agenda setting effects varied dramatically from nonexistent to strong in different issue and event contexts (Neuman, 2016, p.211). The responses of public attention and the media attention to different real-world events are varied, too. To address this variation in the effect size of news agenda setting, public attention scholars have typologized events to build "auxiliary theory" to identify the conditions when an issue or event can influence the relations between news media and public attention (Neuman, 2016, p.212). For example, they categorize events/issues by their obtrusiveness, which shows whether the public is familiar with an event. The public are familiar with the obtrusive events and thus public agenda leads media agenda, yet in the non-obtrusive events, it is the other way around (E. Rogers & Dearing, 1988). Scholars also categorized events and issues by their topic. For example, Neuman and colleagues (2014) tracked 29 political issues and events from news websites, Twitter, blogs, and online forums during 2012, including unemployment, energy costs, finance, and health care (Russell Neuman et al., 2014). Based on their analysis, they found that news media attention predicts public attention for some issues, such as national security, crime, and drugs, whereas public attention (measured as Twitter attention) predicts news attention for other issues, such as gun control, natural disasters, LGBT issues. However, agenda setting scholars have not agreed on which event categorization is the best auxiliary to agenda setting theory.

In terms of the patterns of public attention and the information diffusion processes that explain it, information diffusion scholars found variable patterns too. For example, Nahon and colleagues (2013) found that news media coverage predicts large amounts of online public attention after unexpected events, because those events tend to correlate with repeated peer-to-peer exposure through tweets, retweets, and mentions from Twitter users, but attention quickly wanes afterwards. For other topics, they found less peer-to-peer exposure. In another study, Lehmann and colleagues (2012) tracked 130 million tweets related to different events (measured by 402 unique hashtags) in less than a year. They detected four types of attention patterns of these events—attention concentrated before and during the peak, during and after the peak, symmetrically around the peak, and only on the single day of the peak. Their findings further suggest that the patterns of attention are contingent on whether the mass media or the social interaction drives attention spikes. Specifically, they found that events with symmetric attention patterns across the peak are related to the spread of attention driven by social interactions. Events with attention concentrated during and after the peak are associated with the spread of attention driven by mass media. Romero et al. (2011) found that public attention (using Twitter attention as a proxy) on a range of different topics and events show different process of diffusion. Based on their analysis 3 billion tweets from 60 million users in less than a year span, they found that controversial political events are the most persistent, engaging the public's attention for the longest amount of time.

These findings have illustrated the heterogeneity in the dynamism of public attention across events. Thus, scholars have opened new questions to move forward the theories of public attention. That is, under what conditions does the contemporary media system enable which types of actors to influence public attention (Neuman, 2016, p.20)? Under which conditions do gatekeepers became the gated and when the other way around (Nahon, 2008)? Recognizing the conditions of when power relations between ordinary people and organizations shift is increasingly consequential in determining the flows of public attention (Lazar, 2020). However, Neuman pointed out that communication studies are still at an early stage to recognize these conditions, because the majority of studies still focus on one mechanical model and a "true-false dichotomous notion of theory testing" (Neuman, 2016, p.238). To push forward the theories that explain public attention, scholars should consider carefully describing the dynamism of public attention, both in terms of its patterns and the interactive relationships with other actors across different events.

Summary of Literature

In this section, I summarize the key findings and challenges from the literature review and introduce the main goals of each empirical analysis I conduct in the following chapters.

Synthesizing the two streams of literature that explain the evolution of public attention, it is clear that the communicative activities of organizations and ordinary people can both drive public attention. Accordingly, I offer the following propositions about public attention in hybrid media systems. These initial theoretical propositions are the lenses that guide the empirical studies that follow.

- Public attention can be distinguished from public opinion, news attention, and social media attention in terms of four characteristics: intensity, volatility, sustainability, and cycles.
- Public attention and attention from traditional gatekeepers are mutually shaping.
- Between public attention and elite forms of attention (e.g., news media, politicians, advocacy organizations), the role of gatekeeper and the gated shifts dynamically—the power to spark public attention changes rapidly.
- Patterns of public attention and the causal mechanisms that explain public attention are heterogeneous across high-volume attention events, even within a single issue.

In summary, this literature review suggests two challenges of studying the evolution of public attention in a hybrid media system. First, a standard conceptualization, definition, and measurement of public attention is missing, thereby potentially hindering theorizing on the causes of public attention. Existing studies have most often conceptually and empirically confused public attention with public opinion, news attention, and social media attention. Thus, it is difficult to tell what exactly public attention is, how to measure it and how to theorize it. Second, the evolution of public attention happens in a transmedia environment. That is, public attentiveness evolves as attention changes across media platforms. With the advent of social media such as Twitter, public attention is often the byproduct of the intertwined communicative relationships among elite organizations (e.g., news, political, large organizational actors) and individuals. In other words, public attention is jostling with other forms of attention from different types of actors in a network gatekeeping process, which is rapidly changing over time. Thus, it is difficult to sort out the intertwining, interdependent, and ever-changing relationships between public attention and the other forms of attention in different even contexts.

In this chapter, I have argued that public attention is distinct from other forms of attention (news, social media attention, and public opinion). I conceptualize public attention as a resource that multiple sets of actors compete for to realize their goals in the hybrid media system. For the purposes of the empirical studies in this dissertation, I define public attention as the attention from ordinary people, who do not represent any organizations such as news media, journalists, political elites, or major advocacy groups.

Climate Change Issue: The Context to Study Public Attention

To narrow the scope of this dissertation, I use the climate change issue as the context for the empirical analysis. This issue is suitable for this analysis for three main reasons.

First, public attention to climate change has remained low since it first came into the public eye, at least until recently, when it grew only slightly (Moser, 2010). In general, public attention and understanding of climate has remained relatively unchanged for a long time (Egan & Mullin, 2017). In the United States, Gallup (2017) has consistently ranked it one of the public's lowest concerns. Indeed, economic issues almost always attract more attention than climate change. Furthermore, the nearly seemingly insurmountable economical cost associated with dealing with climate change, only makes climate changes less concerning for me (Scruggs & Benegal, 2012). Additionally, on digital media platforms such as Twitter and Google, public attention has been short-lived after a climate attention event (Hestres, 2015; Thorson & Wang, 2019) and highly polarized by partisanship (Jang & Hart, 2015; Williams et al., 2015). Despite an overwhelming amount of scientific reports that support climate change and endorse human activities as causes of climate change (Cook et al., 2013), the general public disagrees on whether climate change is real, its causes, and what actions should be taken to fix it (Egan & Mullin, 2017). As a result, how to effectively raise attention and sustain attention about climate change are everlasting questions in communication studies of climate change.

Second, the insufficiency of climate change attention and the challenges to climate change communication are related to the characteristics of the issue itself. Climate change is as a remote, complicated (Painter et al., 2018), and unobtrusive topic (Djerf-Pierre & Shehata, 2017; Painter et al., 2018; Schäfer & Schlichting, 2014). To the public, climate change is essentially a complicated scientific problem. Its primary description is in science language, with varied definitions, methods, and measurements. Although scientists agree that anthropogenic climate change exists, contradictory conclusions and conflicting ideas still exist in scientific research about some specific assumptions, measurement, and validity (Schäfer & Schlichting, 2014; Sluijs, 2012). The complicated scientific debates add not only uncertainty to the climate change issue, but also make it even more difficult for the public to understand. Moreover, the climate change issue is a large temporal and spatial phenomenon. According to the World Meteorological Organization, climate change deals with the changes of temperature for at least 30 years (Claussen, 2003, p. 21) in the entire continent, hemisphere, or the entire world (IPCC, 2007, P11). As such, a core challenges of climate change communication are how to best convey the gravity of temporal and geographical changes, which are far beyond the cognizance of people's real-life experience (Schäfer & Schlichting, 2014). The human mind may not have evolved enough to understand the complexities of deep time (McPhee, 1998) and space. As for the effects of climate change, they are often invisible, uncertain, and far away from people's daily lives. Instead, the consequences of climate change only happen in the future (Egan & Mullin, 2017). The vulnerability to climate change of each country is also different, more adversely affecting countries outside United States and Europe (Egan & Mullin, 2017).

Third, the climate change issue is a long-term issue that involves a wide set of actors, including politicians, government organizations, news media, and various other organizations (Cody et al., 2015). Thus, this issue is a prime context to study the dynamics of public attention and the impact of multiple sets of actors over a long period. For a long time, newspaper and TV were considered the two major sources of attention related to climate change (Boykoff, 2008; Tandoc & Eng, 2017). As people's media consumption behavior has changed from traditional media to digital media, now, digital media have gradually become more relevant to climate change communication. A growing number of studies have started using digital media as a valuable resource to trace the transmission of climate change attention, conversations, and public discourse. For example, Kirilenko and Stepchenkova (2014) monitored a year of tweets from users across the world to trace public perception of climate change. Veltri and Atanasova (2017) examined the diversity of actors who circulating climate change information on Twitter.

Williams et al. (2015) noted that an echo chamber exists within the climate change communication networks, where people only communicate with like-minded actors on Twitter about this issue. Several other studies focus on climate change advocacy groups and how they have used Twitter to mobilize ordinary people and generate substantial public attention for climate change events (Bennett & Segerberg, 2011; Thorson et al., 2016). In sum, this issue involves a variety of actors and media outlets, making it a prime example to use for empirical analysis. In the next chapter, I conduct an empirical analysis to examine how public attention is distinctive from other forms of attention and their relationships over the time.

CHAPTER 3: PUBLIC ATTENTION TO THE CLIMATE CHANGE ISSUE: PATTERNS AND TEMPORAL RELATIONS

Following my argument in Chapter 2, I propose that public attention is a distinctive category of attention from news attention, social media attention, and public opinion. Yet many existing studies have empirically confused these forms of attention as an operationalization of public attention. Therefore, the first goal of this chapter is to empirically demonstrate the limitation of doing so in terms of theorizing the evolution of public attention. Moreover, prior studies about climate change attention have shown that agenda setting from news and agenda building from strategic organizations have played a leading role in shaping public attention to the climate change, whereas more recent studies have suggested the importance of social media in mobilizing public attention to climate change events. Thus, the second goal of this study is to tease out causal relationships among the different types of attention.

In service of the first goal, I examine how public attention is different from public opinion, news attention, and social media attention. I collected daily and monthly time series data from the news media, Twitter, and public opinion polls, alongside Google search data. I create empirical comparisons among the types of attention based on four characteristics of attention (intensity, volatility, sustainability, and cycles). As for the second goal, I examine how public attention temporally corresponds with other sources of attention (e.g. news attention, social media attention, and strategic organizational attention) that could potentially cause it. Here, I use daily and monthly times series data from news media, Twitter, Google search, and press releases. I then conduct time series to find out the temporal relationship among public attention, news attention, social media attention, and strategic organizational attention based on two temporal aggregations—daily and monthly.

In terms of my first goal, I show empirically that public attention is different from news attention, social media attention, and public opinion. Regarding my second goal, I find substantial differences in terms of the pace of attention influence across platforms. Twitter is a "fast" platform that is associated with intensive, volatile, but transient spikes of daily attention. Among the platforms I examined, Twitter is most likely to produce the most changes in the public attention to the climate change issue, but its impact is short-lived. In contrast, news attention produces long-term changes in the public's attention to the climate change issue.

This chapter extends the current literature about public attention and intermedia diffusion of attention in three ways. First, the findings from this chapter affirm my argument about the necessity to treat public attention as an independent analytic category. News coverage, Tweets, and public opinion polls are not the best measurement of public attention. Second, Twitter is the platform most likely to produce changes in the public's attention to climate change, but its impact is short-lived. In contrast, news attention produces long-term changes in the public's attention to climate change. This finding challenges communication theories such as agenda setting and agenda building that were based on a media environment where public attention evolved in a much slower pace. Lastly, the chapter contributes to the methods of using different temporal-aggregated data to detect the heterogeneity in the dynamism in public attention and other forms of attention.

In what follows, I first introduce the literature and the publicly available data that allows me to test the differences among the patterns of public opinion, news attention, social media attention in terms of their long-term trends and their responses to climate change events. Then, this chapter proceeds by three sections, each focusing on the role of news media, social media, and intermedia agenda setting in explaining the evolutions of public attention across media.

Following that, in the method section, I introduce a robust way to measure public attention. In particular, I discuss the challenges of measuring public attention and the ways to transform and validate the search queries from Google Trends to represent climate change attention. Then, I present the data collection, analytic methods, and results. Finally, I outline the theoretical implications of the findings.

Patterns of Climate Change Attention

In Chapter 2, I pointed out that public attention has been commonly conceptualized and operationalized as equivalent to public opinion, news attention, and social media attention. To explain the limitation of doing so, this section briefly conducts a literature review on the differences among the patterns of public opinion, news attention, and social media attention to climate change. I use Twitter as a representative of social media as it is the most studied media platform so far in the research about online climate change communication (Pearce, Holmberg, Hellsten, & Nerlich, 2014). I first focused on the long-term trends of public opinion, news attention, and social media attention, and then focused on their responses to climate change events.

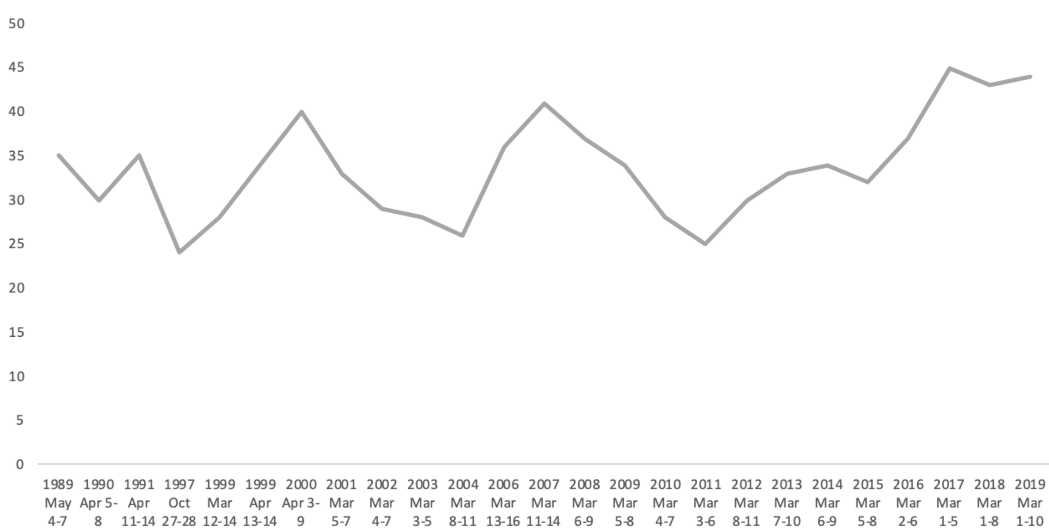
Long-term Trends in Attention to the Climate Issue

This section compares the long-term trends of public opinion, news attention, and Twitter attention to the climate change based on the findings from existing studies and publicly available data.

The proportion of the U.S. public that perceives climate change as an important issue to the country remained low until recently. Anthropogenic climate change first came to public attention in 1980s (Moser, 2010). Over the last 40 years, however, public opinion lacks meaningful long-term change and people care even less about the issue during times of economic crisis (Egan & Mullin, 2017; Scruggs & Benegal, 2012). Figure 1 illustrates this trend. It shows the proportion of the U.S. public who reported worrying about climate change and global warming from 1989 to 2019. A close reading of this graph shows two clear cycles in the public's concern about climate change. Specifically, in the early 2000s following the collapse of the dot-com bubble and amid the Great Recession, public opinion about climate change plummeted. As the economy gradually rebounded from these events, public opinion about climate change steadily increased. Illustratively, while only a quarter of the general public reported worrying about climate change in 2011, by 2019, almost half did (Gallup, n.d.). Other research upholds these trends. Considering public concern about climate change globally, Pew Research (2019) reports that since 2013, the public has increasingly become more attentive or concerned about climate change. In fact, most people across the world consider global climate change a major threat.

Figure 1

The Trend of Public Opinion about the Climate Change and Global Warming, 1989–2019



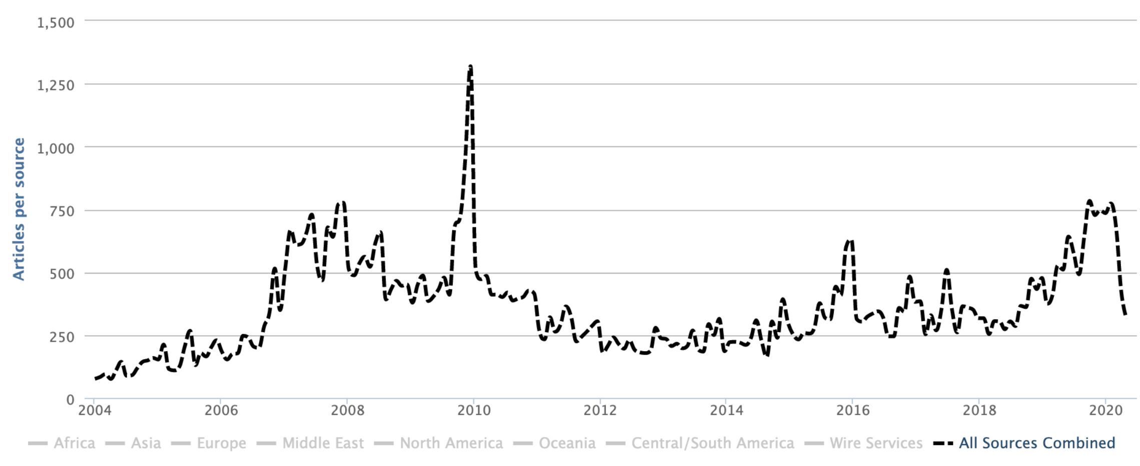
Notes: The figure shows the annual percentage of people who reported to worry about climate change or global warming at a great deal in the U.S. from 1989 to 2019. I created the table with the data retrieved from the link (https://news.gallup.com/poll/1615/environment.aspx).

Despite recent shifts that show more people in the U.S. perceive climate change as an important issue, public opinion shows strong partisan and ideological polarization (Egan & Mullin, 2017). Over the past six years, the number of Democrats and Democratic leaners who are concerned about climate change grew by 25 percent, yet for Republicans and Republican leaners, there has been only a 5 percent growth. In 2018, a total of 83% of Democrats indicated that climate changed was a major threat, whereas only 27% of Republicans thought so.

In contrast to the public opinion data, the long-term trend of news attention looks quite different. Drawn from data on global news coverage on climate change and global warming from 2004–2020, Figure 2 shows that news attention on this topic rapidly increased from 2006–2008 and reached a dramatic peak at the end of 2009—the year of the United Nations' Climate Change Conference in Copenhagen. Afterward, news media coverage starkly decreased and remained relatively low until 2018, at which point it began to increase again.

Figure 2

The Volume of Newspaper Coverage of Climate Change and Global Warming, 2004–2020

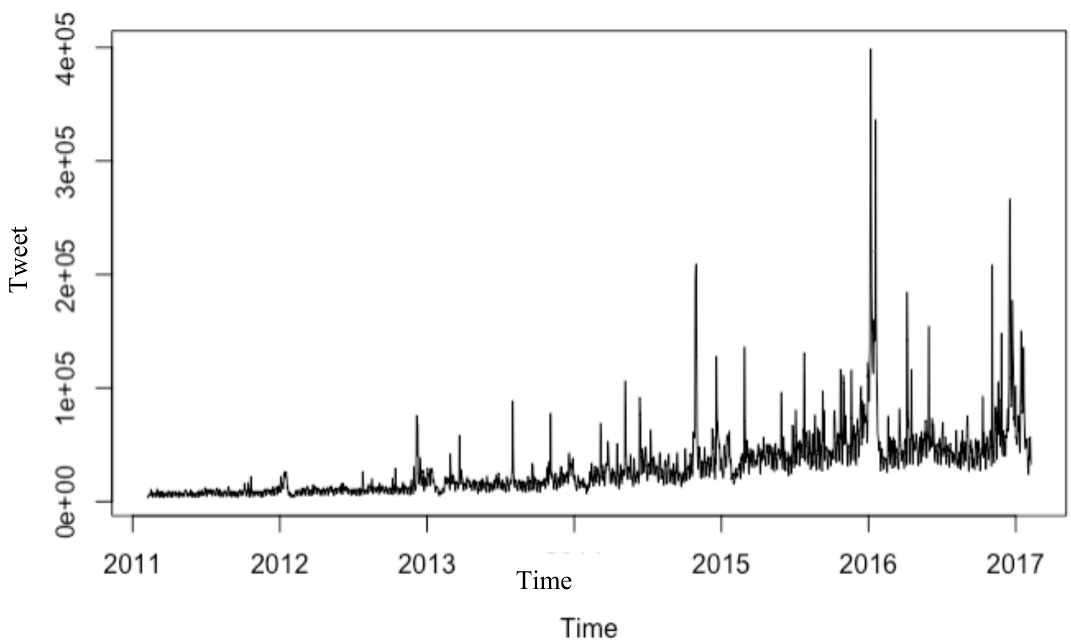


Notes: The figure was based on data from Media and Climate Change Observatory (https://sciencepolicy.colorado.edu/icecaps/research/media_coverage/world/index.html).

The pattern of Twitter attention, measured by volume of tweets, also does not align with public opinion. Somewhat mirroring the growing news media coverage of climate change, the climate issue has also gained increasing attention on Twitter from 2011 to 2016. Based on the trends of the daily volume of tweets related to climate change (see Figure 3) from Thorson and Wang (2019), Twitter attention to climate change continues to grow[4], with more dramatic short-term increases than either news or public opinion.

Figure 3

The Number of Tweets About "Climate", 2011–2016



Notes: I produced the figure based on the data from Thorson and Wang (2019). It shows the daily number of tweets from 2011–2016 about climate change attention. To plot out the trend of Twitter attention, they ran a search on Crimson Hexagon using the term "climate".

In summary, the long-term trends of public opinion, news attention, and Twitter attention to the climate change issue are all different. The data suggests that public opinion of climate

[4] after adjustment of the growth in Twitter users.

change has stayed relatively stable over time, but news coverage and Twitter attention on this issue has ebbed and flowed. Therefore, confusing public attention with any of these three forms of attention may result in misinformed or inaccurate understanding of the trend of public attention, as I illustrate below in detail.

Climate Change Attention and Real-Life Events

Chapter 2 has conceptually identified public attention, news attention, social media attention, and public opinion. To reveal their empirical difference, this section reviews existing studies about public opinion, news attention, and Twitter attention to the climate change issue in terms of how they respond to the real-life events that relate to climate change.

Studies have shown that public opinion is stable and often either unaffected or only moderately affected by climate change events (Newig, 2004; Ripberger, 2011). Agenda setting studies categorize climate change as an non-obtrusive issue, which the public cannot directly experience (Djerf-Pierre & Shehata, 2017; Neuman, 1990). Echoing with agenda setting studies, the majority of climate change communication scholars have perceived the issue as essentially a scientific problem that remains to be complicated and remote in the public's daily life (Painter et al., 2018; Schäfer & Schlichting, 2014). Therefore, the public opinion is less likely to have dramatic change due to the events related to the climate change issue. Moreover, economic development and unemployment are likely to downplay the importance of climate change issue. As mentioned earlier, the number of people who show concern about the climate change issue tends to decrease during economic crises (Egan & Mullin, 2017). Scruggs and Benegal (2012) found that economic concerns likely contributed to declining concern about climate in the United States and European Union from 2000–2011. Further, they found that although people often cite partisan polarization, biased media coverage, and weather changes as reasons for shifts in public opinion, these factors did not correlate with changes in public opinion about climate change. Accordingly, the study argued that people likely prioritized current economic concerns over more long-term issues like climate change.

In contrast to public opinion, the news media tend to be more sensitive to short-lived surges in attention to different kinds of climate change events. News attention responds to events like international conferences organized by large intergovernmental organizations and extreme temperature changes (Jones-Jang et al., 2020), disputes between politicians and scientists (Brossard et al., 2009), and climate change disasters (Castillo, El-Haddad, Pfeffer, & Stempeck, 2013). Even so, high levels of news attention to climate change events are only short-term, as shown by a study from Lörcher and Neverla (2015). They systematically compared how different types of media responded to two climate change events—the 2013 United Nations Climate Change Conferences and the release of the 5th Intergovernmental Panel on Climate change (IPCC). Based on their analysis, they found that news media paid more attention to both events than social media platforms. But the news attention quickly shifted and decayed soon after the two events happened.

Compared to news media, Twitter responds to broader categories of climate change events, often with dramatic surges of attention that are transient and fragmented. Some studies have found that climate change-related events tend to be the biggest trigger of dramatic changes in Twitter attention (see e.g., Cody et al., 2015; Soroka, 2002; Thorson & Wang, 2019). In addition, Twitter also responds to some minor daily life events. For instance, tracking millions of tweets from 2008–2014, Cody et al. (2015) found that small events like a book release or weather changes seemed to fuel Twitter users' attention to climate change. Despite the fact that Twitter attention shows a stronger response to more climate change-related events, it is ephemeral—similar to the news attention—and fragmented. By observing 11,838 tweets related to an Avaaz[5] campaign before the release of the 2013 IPCC report, Holmberg and Hellstern found that attention to the campaign quickly peaked and then decayed right after the release of the report. In a study of the People's Climate March in 2014, Thorson et al. (2016) found that when attention reached its peak during the protest, Twitter volume was high but full of fragmented attention about different aspects of the climate change event.

In summary, public opinion, news attention, and Twitter attention each show a distinctive response to real-life events related to climate change. Public opinion tends to show an inertia to climate change events because of their remoteness and non-obtrusiveness to the public, whereas both news attention and Twitter attention tend to be more sensitive to more categories of climate change events than public opinion. Twitter attention seems to be particularly more dramatic, short-lived, and fragmented than news attention. All these findings suggest that equating public attention with any of the three forms of attention would lead to different or contradictory results. Echoing my argument in Chapter 2, public attention conceptually different from public opinion, news attention and social media attention. To empirically demonstrate the limitation of operationalizing public attention as using public opinion, news attention or social media attention, I draw on the four attributes of attention (sustainability, volatility, intensity, and cycles) that I proposed in Chapter 2 and ask:

RQ1: How is public attention to the climate issue different from public opinion, news attention, social media attention, in terms of its intensity, sustainability, volatility, and cyclical nature?

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[5] Avaaz is an advocacy organizational that orchestrates global online movement

News Media as a Cause of Public Attention

In addition to characterizing the different temporal patterns across types of attention, the second goal of this chapter is to begin to tease out causal relationships among the different type of attention. This section reviews literature about the role of news media in generating public attention about climate change. A large body of literature has shown that news media determines climate change attention. These studies support propositions based on agenda setting theory (McCombs & Shaw, 1972) and, in particular, how the theory can explain the evolution of public attention to climate change. As mentioned earlier, the climate change issue is a non-obtrusive and remote issue, and people are rarely, if ever, directly affected by climate change in their everyday lives. Therefore, news media have become ‘‘important agents in the production, reproduction, and transformation of the meaning” of anthropogenic climate change (Carvalho, 2010, p. 172). Plainly, the news serves as an important source for people to learn about climate change (McCombs, 2005), as it helps distill scientific research on this issue (Carvalho, 2010; Tandoc & Eng, 2017) and makes clearer the tangible implications of climate change (Boykoff, 2011). Through these framing processes, news media can mobilize public attention and emotion—cognitive and affective responses—to climate change (McAdam, 2017).

Existing studies suggest that news media influence both public and social media attention. Social media still depends on mass media for climate change information. Illustrating this relationship, Kirilenko and Stepchenkova (2014) observed 1.8 million tweets about climate change and global warming from 2012–2013 and found that Twitter attention to climate change was strongly correlated with news reports on this topic. Similarly, Veltri and Atanasova (2017) found that social media attention to climate change highly depends on newspaper and public broadcasting news media coverage. Nonprofits and political elites used news media to express their climate change opinions in an attempt to sway the public to align with to their interests (Nisbet & Mooney, 2007). Comparing 15 years of news reports about climate change in Australia, Germany, and India, Schäfer et al., (2014) found that environmental nonprofit organizations and political actors worked diligently to generate news attention for international climate change events. However, these efforts were not in vain; news media respond to pressures from these different organizations far more so than they do to real-life weather changes, which evidence the reality of climate change (Schäfer & Schlichting, 2014). Andrews and Caren's (2010) study affirms these findings. Specifically, they found that formal nonprofit organizations can influence local news attention on climate change by press release, particularly when they mobilize the public attention (Andrews & Caren, 2010).

Despite the importance of news media in climate change communication, scholars have criticized news media for not generating enough public attention. First, scholars bemoan that fact that rather than clarifying the complexities of the climate change issue, news coverage amplifies the debates and uncertainty within this body of scientific research (see e.g., Boykoff, 2008, 2014). Journalistic norms of balancing news reports downplays the scientific consensus about anthropogenic climate change (Feldman et al., 2012). Journalists also tend to blame the uncertainty surrounding climate change on scientists (Boykoff, 2008). Boykoff (2001) sums up this line of criticism of news media well by essentially saying that they have failed to educate citizens and policy actors about the scientific truth of climate change.

Second, scholars criticize news media for politicizing and polarizing the issue. Rather than emphasizing scientific research, news coverage often focuses on political claims and policy debates on the issue (Boykoff, 2011) and calls on increasingly more political actors than scientists to speak on this issue (Chinn et al., 2020). For instance, analyzing U.S. major newspaper from 1985–2017, Chinn et al. (2020) found that media representation of climate change was increasingly politicized and polarized. Telling of the politicized nature of climate change is the disparate ways different news outlets present this issue. Appealing to different audiences, Feldman and colleagues (2012) found that conservative media (i.e., Fox News) presented a more cavalier tone about climate change than nonconservative media outlets, such as CNN and MSNBC. In this way, partisan media can mislead the public about climate change and foment increasing polarization concerning climate change, as people tend to consume media that aligns with their views and interests. (Feldman et al., 2012; Feldman, Myers, Hmielowski, & Leiserowitz, 2014). When people treat broadcast media as their main trusted source of information about climate change (Schäfer & Schlichting, 2014), this polarization presents a major challenge to strategically raising public attention and consensus about climate change.

Third, scholars criticize news media for concentrating on major environmental organizations who tend to mobilize large groups of people, while neglecting the grassroot efforts from smaller, less organized advocacy groups (Thrall et al., 2014b). Andrews and Caren (2012) found that news media payed little attention to advocacy groups spearheaded by temporary volunteers, which used confrontational advocacy strategies focused on novel environmental issues. Based on journalism routines, news media prefer established organizations that were sure to create news value. Specifically, news media prefer organizations that are "larger, proximate, and address issues of greater social significance" (Andrews & Caren, 2010, p. 844). However, the news media's preference for covering stories and issues of immediate and proximal concern (Trilling, Tolochko, & Burscher, 2017), particularly among such media outlets in high carbon emission countries (most of which are also highly developed countries), may blind the public to the ways that climate change negatively affects human development, particular in developing countries. News media in developed counties often view climate change as a far off, distal concern—an issue affecting comparatively less developed countries. As such, these outlets overlook how climate change affects countries in South America, South East Asia, Pacific Islands, and Africa. These countries tend to be the most vulnerable places to climate change (Archibald & Butt, 2018).

In sum, studies show that news media plays a critical part in shaping public attention to climate change, serving as a major source of information about this issue for the public as well as for other media outlets, such as social media. Additionally, political actors play a key role in shaping the climate change agenda by influencing news attention. At the same time, however, news attention fosters a sense of confusion or distrust of relevant scientific research on climate change and politicizes this issue, so much so that polarizes the public's views about climate change and what do about it. With the widespread adoption of social media, could it raise more public attention about climate change? Scholars have just started considering this question.

Social Media as a Cause of Public Attention

This section reviews literature about the role of social media in generating public attention about climate change. Social media platforms, such as blogs, Facebook, YouTube, Twitter, and Weibo, provide a space for information, discussion, and mobilization of climate change (Tandoc & Eng, 2017). As such, with the rise of social media, many climate change advocates and researchers hope to mobilize the public and increase its attention to this issue (Hestres, 2014, 2015). Pearce et al., (2019) perceived social media as an outlet that can disturb existing media power structures largely controlled by traditional gatekeepers and involves everyday people. This increasing mass of ordinary people participate in generating news and bringing attention to different issue areas, including climate change. Affirming this point, Wang et al. (2019) found that social media engages a variety of organizational and individual actors, such as scientists, small civic advocacy groups, and individual climate change activists. With increasing content circulating on social media, the public has access to more information on climate change (Schäfer & Schlichting, 2014) and can help spread this information to others through their social networks (Boykoff, 2011).

A growing number of studies support the hope that the growth of social media can engender more public attention to issue of climate change. Scholars in these studies have used social theories to explain the production and diffusion of public attention to the climate change issue. For example, Wang et al. (2019) applied Lave and Wenger's (1991) community of practice theory to examine the roles of individuals and organizations who participated in Twitter discussions about climate change across a series of climate change related events over a stretch of time. Based on this theory, individual attention to climate change depends on group members' attention to this issue across the individual's online communication networks and/or social networks. Thus, sustained Twitter attention to climate change can cultivate individual attention to this issue, which eventually may heighten public attention to climate change (Wang et al., 2019). Other studies, informed by Lazarsfeld et al.'s (1948) two-step flow model, likewise find evidence of the power ordinary people have in affecting public attention. For example, Shapiro and Park (2018) analyzed the network of comments from the most viewed YouTube videos about climate change and found that a small group of opinion leaders—regular YouTube users—dominate the comment boards, even though established organizations produced most of these popular videos. By tracking tweets using climate change hashtags the days immediately before and after the release of the IPCC report, Newman (2017) found that individual bloggers and citizens attracted most attention as they showed up in the top 100 most retweeted users. That is, these everyday people were the most successful at leveraging their social media presence to spread information and awareness about climate change and, in turn, increase attention to this issue. In short, these findings indicate that informal peer-to-peer communication on social media can have demonstrable impact on the spread of information and in swaying public attention.

Given the power of social media to influence public attention, strategic organizations on climate change have actively used it to mobilize public attention to climate change events (Hestres, 2014, 2015). For example, Segerberg and Bennett (2011) analyzed the connectivity and the sources of tweets related to the climate change protests held during the 15th United Nations Conference of the Parties on Climate Change (COP-15) in 2009. They found that advocacy organizations encouraged climate change activists to use specific hashtags to accelerate the mobilization for their agenda. They concluded that Twitter acts as a “stitching mechanism” that connects attention across diverse networks (Bennett et al., 2014; Segerberg & Bennett, 2011b). Thorson et al., (2016) examined the tweets related to the People’s Climate March in 2014 and found that Twitter enabled climate change activists, both individuals and organizations, to build public attention to these real-life protests and create ad hoc publics, who were all concerned about the climate change issue and thread together a variety of orientations to the issue. Stier et al. (2018) analyzed climate change policy debates on Twitter and found that dramatically increased attention to climate change raised political elites attention to this issue, leading them to consider, propose, and enact new policies.

In sum, research on social media attention to climate change suggests that social media is a new space for raising climate change attention. Ordinary users can spread climate change attention and influence others. Strategic organizations have used Twitter to mobilize public attention and influence political elites. Indeed, other actors, besides traditional news media outlets and large established organizations, influence public attention surrounding climate change—and Twitter may be an important engine for facilitating the visibility of these other actors.

The Intermedia Transfer of Climate Change Attention

There is a bifurcation in the literature between studies of news media attention to climate change and those of social media attention. Most climate change communication studies exclusively focus on one type of media—either news media or social media. Only a few examine the distribution of climate change attention across both social media and news media (i.e., newspaper, TV, and news websites). These handful of studies use intermedia agenda setting theory to explain the process. In general, these studies show that news media attention and social media attention predict each other, but which one follows the other and the importance of their respective effects vary over time. For example, Jang and colleagues (2020) analyzed the contagion of climate change agenda and frames across Twitter and online news media from 2015–2017, finding that both these media types shaped the other's agenda and frames about climate change. In another study, Yan and Borah (2019) examined how public attention flowed between Twitter and newspapers when Donald Trump announced the U.S.'s withdrawal from the Paris Agreement. Tracking tweets and newspaper coverage immediately preceding and following this announcement, Yan and Borah found that news attention preceded Twitter attention before the announcement. However, news attention later followed Twitter's attention. Accordingly, they concluded that Twitter likely prompts news attention shortly after the occurrence of breaking news, while news attention likely directs Twitter users to topics that drive ongoing debates; and the impact from Twitter on news was not long lasting.

Altogether, news media, social media, and strategic organizational actors all shape public attention surrounding climate change. News media, social media, and strategic organizational actors also correspond with each other across media. Consequently, I hypothesize:

H_1: Attention from news media, social media, and strategic organizational actors predicts public attention to climate change over time.

H_2: Attention from news media, social media, and strategic organizational actors mutually predicts each other over time.

Furthermore, I raise a question as to whether media effects on attention hold at different levels of temporal aggregation. Wells et al. (2019) explains temporal aggregation as the practice of increasing the unit of analysis for time series data. Low levels of temporal aggregation result in smaller and high frequency of time units, whereas high levels of aggregation result to larger and low frequency time units. As mentioned in Chapter 2, agenda setting studies emerged in a time when the media environment followed a much slower pace than today. Therefore, in studying public attention, these scholars often aggregated temporal data at a high level to examine accumulated media effects. For instance, the unit of analysis in Su and Borah's (2019) intermedia agenda setting study is days, and in Jones-Jang et al.'s (2020) study, it is by weeks. But higher levels of aggregation of time series data (e.g., monthly) eases the temporal dynamics which low levels of aggregation observation can reveal (Shellman, 2004). Therefore, I ask:

RQ2: How do H_1 and H_2 vary with different temporal aggregations?

Method

In the method section, I first introduce a robust way to measure public attention using Google Trends Index. I also point out two challenges of using Google Trends Index as a measurement to public attention: noise from the data and the choice of search queries. I then walk through the data collection process and the sources of data that I used for analysis. Finally, I introduce the approach to operationalize the four attributes (intensity, sustainability, volatility, and cyclical natures) and the time series analysis to examine the relationships between different forms of attention over time.

Measurement of Public Attention

Digital media provide valuable resources to trace public attention to climate change over time. Google Trends data is one such resource. In real-time, Google anonymously aggregates users' search queries into categories, meaning this data is constantly updating (Salganik, 2017). As such, people view this data as representative of real-world users' Google search behavior.

Google Trends data create opportunities and is an alternative way for researchers to understand the dynamics of public attention to climate change events. Again, since Google automatically refreshes this data, it is easy to track any changes in climate change attention preceding or following a climate change event. While enabling such tracking of public attention, these data are also free, providing a far less expensive means of conducting longitudinal research. Furthermore, these data do not reflect people's self-reports of their attention or survey conductors' interpretations of people's attention—two potentially biased measurements (van Atteveldt & Peng, 2018). With all these benefits, increasingly more researchers use these data to measure climate change awareness. For example, Anderegg and Goldsmith (2014) used Google Trends data to reflect public attention to climate change. In yet another study, Archibald and Butt (2018) argued that Google Trends data served as a valid proxy for public awareness about climate change.

Given that Google's market share is as high as 87% (Statista, 2020), with users across the globe, many scholars use Google Trend data as a proxy index for public attention (see e.g., Anderegg & Goldsmith, 2014; Kwak, An, Salminen, Jung, & Jansen, 2018; Ripberger, 2011) or for issue salience (see e.g., Mellon, 2013, 2014). Emerging studies have shown up using Google Search data to study the public attention to politicians during the elections (Swearingen & Ripberger, 2014), predict the influenza epidemics (Ginsberg et al., 2009), or track public attention to important issues in general (e.g., Anderegg & Goldsmith, 2014; Archibald & Butt, 2018; Herrnstadt & Muehlegger, 2014; Mellon, 2013, 2014; Qin & Peng, 2016; Ripberger, 2011). Considering these positives and the its increasing use among researchers, in this present study, I likewise use Google Trends data.

Although Google Trends is a robust way of measuring public attention, it is not perfect. In fact, using this data presents two major challenges. The first challenge is to control the noise in the data. The second is about the choice of search queries.

Noise in the Data

The first major challenge presented by Google Trends data is its noise, resulting from potential algorithmic confounds. In terms of the former, Google normalizes it Trends Index from 1–100 to indicate the popularity of a search query, rather than reporting the actual frequency of a given search query. Further complicating this issue, Google does not release the algorithms it uses to normalize this index. Therefore, aggregating or comparing search trends between or among different queries becomes problematic, as those may be differently scaled (Lazer et al., 2014). To mitigate this issue, I followed an approach used in other studies (Qin & Peng, 2016; J. J. H. Zhu et al., 2012). Specifically, I transformed the daily index with a benchmark query—a randomly distributed white noise query that always exists. I calculate the fraction between the daily index of the two search queries and the daily index of the benchmark query. I discuss more about the benchmark query in the data collection section.

Choice of Search Query

The choices of search queries became the second challenge. Search queries change all the time. For example, when people search for climate change, they do not just use the term "climate change." Some scholars take a data-driven approach in response to this issue. For example, in their study on influenza, Ginsberg et al. (2009) designed an automated method that would extract all related search queries about influenza. Distilling 50 million candidate queries, they identified the 45 most relevant search queries. However, many scholars questions this painstaking approach because it may increase the likelihood of identifying false correlations due to the high number of tests (Mellon, 2014) and lead researchers to overfit data (Lazer et al., 2014).

In light of this concern, to make decisions about search queries, I follow Anderegg and Goldsmith's (2014) methods. I compared the Google Trends index of the candidate search queries I chose with public opinion data from Gallup in OLS regression. Although public attention and public opinion are distinct constructs, I can use public opinion to help make decisions about the choice of search queries. I discuss the choice of search queries and validation in the data collection section below along with the other results of this analysis.

Data Collection

To contrast the patterns and run the time series analysis, I collected data from multiple sources. For the social media attention, I used Twitter data as a proxy for social media attention regarding climate change. However, the Twitter streaming API and search API do not return full data of daily volume of tweets. Therefore, I used Thorson and Wang's (2019) data from 2011–2016 on the daily number of tweets about climate change attention. Running a search on

Crimson Hexagon using the term "climate", Thorson and Wang collected over 66,056,382 tweets, which I included within my dataset.

In terms of the attention from strategic organizational actors, I collected 7,858 daily press releases from PR Newswire from 2011–2016. In terms of the measurement to news attention, I collected 518,934 daily news coverage about climate change written in English and published in newspapers from 2011 to 2016, using LexisNexis. I used the terms "climate change" and "global warming" to run these searches. I used beautifulsoup4, a Python library to extract the publishing time and titles of the news articles.

I also collected public opinion data from 2011–2016. I collected responses to Gallup's monthly Most Important Problem survey in which they ask U.S. participants "What do you think is the most important problem facing the country today?" I calculated the monthly percentage of people who chose "environment/pollution" as the most important problem affecting the country.[6]

Lastly, I collected Google Trends Index data to measure public attention. I first examined the most correlated queries for "climate change", using the function command "`related_queries`" in the gtrendsR package (Massicotte, 2019). I found that since 2004, the earliest time point that I can trace back in Google Trends, "climate change" has been most correlated with "global warming". Then, I ran two queries in Google Trends, one for the term "climate change" and one for term "global warming" and collected global Google Trends data for these queries for a 6-year period—from 2011–2016. Google Trends returned normalized data representing the relative search volume for each query from 0–100. I will explain the validation of search queries later.

[6] Since data for every June and December during this period were missing, I estimated the monthly percentages using the compound growth rate derived from existing data.

Bringing it altogether, to answer RQ1, which is about comparing the four attributes (i.e., intensity, sustainability, volatility, and cyclical changes) of public attention, public opinion, news attention, and social media attention, I use four data sources (Google search, news coverage, public opinion, and Twitter). To test H_1, H_2, and RQ3, which are all about the temporal relationships among different forms of attention, I use four data sources (Google search, news coverage, press release, and Twitter data). The press release data is not included in RQ1 because previous studies have rarely used strategic organizational attention as a proxy for public attention. To answer RQ3, I aggregated all the data to both daily time units (except for the public opinion poll, which only has monthly data available) and monthly units. The final data includes the daily volume of tweets, news coverage, press releases, and Google Trends Index, representing 2,192 data points; the other dataset includes the monthly volume of tweets, news coverage, press releases, and Google Trends Index data. representing 72 data points. I normalized each time series data into Z-scores for further analysis. The Z-score from a datapoint shows its distance (measured in standard deviation units) from the mean.

Transforming Google Search Queries

As mentioned earlier, the noise in the data is one of the challenges of using Google Trends as a measurement for public attention. Following the method in (Peng & Qin, 2017), I set the search term, “the,” as my benchmark query and collected the daily search index of “the” over this period, per the guidance on selecting benchmarks—that they be stable and predictable searches (Qin & Peng, 2016). Using this benchmark data, I transformed my normalized Google Trend data. Specifically, I normalized each time series data by dividing the daily index of each query by the benchmark’s daily index, which yielded a daily query fraction for each respective search item—climate change and global warming.

Validation of Google Search Queries

The other the challenges of using Google Trends as a measurement for public attention is about the search queries. Although the two search queries, “climate change” and “global warming” have been highly correlated with each other over time, it is not yet known that whether using one of the two queries or both queries would lead to any biased results. Thus, I validate “climate change” and “global warming” by contrasting them with Gallup’s MIP data in OLS regression. Since the available Gallup data only measures the monthly U.S. public opinion to the environment issue, I also split out the search behavior from the US (vs. all other countries) in the Google Trends data that I collected.

To validate the two search queries, I used Gallup’s MIP data to predict each transformed Google Trends Index (see Table 1) in OLS regression. The results suggest that it is best to use both “climate change” and “global warming” as search queries to capture climate change attention. As shown by the OLS regression results from Table 1, Gallup’s MIP data is positively correlated with the Google Trend index of “climate change” both in the United States, ($\beta = 0.59$, $p < 0.05$) and across the world ($\beta = 0.4$, $p < 0.05$). Gallup’s MIP data explains 34% of the variance in the search trend of “climate change” at the U.S. level and 14% of the variance at the global level. However, MIP data has no relation with the search index of “global warming” ($\beta = -0.19$, $p > 0.05$) and is negatively correlated with the aggregated search index, which combined both “global warming” and “climate change” ($\beta = -0.36$, $p < 0.05$). Gallup’s MIP data only explain 2% of the variance in the search trend using “global warming”. It is likely that part of the search behavior also came from the climate change doubters. Based on two studies (Jang & Hart, 2015; Zhao, Leiserowitz, Maibach, & Roser-Renouf, 2011), climate change doubters tend to use “global warming” more than “climate change”. Therefore, I used both “climate change” and "global warming" in the Google Trends Index to measure public attention, as it is likely that they represent the research behavior from different groups of people.

Table 1

OLS Regression Using Gallup's MIP Data to Predict Each Search Trends

	climate change (global)	global warming (global)	climate change+global warming (global)	climate change (US)	global warming (US)
Predictor: Gallup's MIP -coefficient	0.4*	-0.19	-0.36*	0.59*	0.20
R^2	0.14*	0.02	0.12*	0.34*	0.03

Notes: * indicates statistical significance at the level of $p<0.05$.

Analytic Method

I used multiple analytic techniques to answer research questions and test hypotheses. I first introduce how I operationalized the four attributes to answer RQ1. I then introduce the time series analysis that I conducted to answer H1, H2, and RQ2.

Operationalization of Four Attributes

As a reminder, RQ1 asks how public attention is different from public opinion, news attention, social media attention, in terms of its intensity, sustainability, volatility, and cyclical nature. I operationalize *intensity* as the maximum number of the Z-score value of time series data representing each form of attention. I operationalize *volatility* as the Coefficient of variation of each time series. The Coefficient of variation is the ratio of the standard deviation to the mean. It shows a unitless standard deviation for comparing data with different units. I operationalize *sustainability* as the number of lag differenced terms that a time series data needs to significantly predict itself in an autoregressive model. I use the formula for Augmented Dickey-Fuller Tests (which is basically an OLS regression) to identify the number of lag differenced terms. Basically, the number of lag differenced terms in an ADF test show for how many time units a time series can still respond to its past values. In other words, the number of lag differenced terms shows the memory of a time series. For more details and explanation of the formula, please see Appendix A.

I operationalize *cycles* as the seasonality of a time series data. To examine the *cycles* of each form of attention, I follow the approach from previous studies (see e.g., Anderegg & Goldsmith, 2014; Mellon, 2014). I plot out each time series data by applying Seasonal-Trend decomposition using LOESS (STL). It is an algorithm that divides up a time series data into three components—its trend, its seasonality, and the residuals from the data after removing the trend and seasonality (Cleveland, Cleveland, McRae, & Terpenning, 1990). I use an R command `STL` in stats package to decompose each time series data and plot the seasonality.

Vector Autoregression Model

As a reminder, H_1 hypothesized that attention from news media, social media, and strategic organizational actors predict public attention to climate change over time. H_2 hypothesized attention from news media, social media, and strategic organizational actors mutually predict each other over time. I follow the approach in Qin & Peng (2016). I conducted Vector autoregression (VAR) models, with Granger causality and Impulse Response Functions as two follow-up analysis using Stata[7].

A VAR model is a multivariate time series model that examines the pairwise relationships among endogenous variables in a system, while controlling for the historic value of

[7] Considering that different analytical tools may bias results, I also used VARS, an R package to conduct the analysis and obtained similar results.

each variable and the exogenous variables (Freeman et al., 1989; Sim, 1980). A VAR model is essentially a set of OLS models, each model predicting the current value of a variable using its past lags and the past lags of other variables. The endogenous variables are the Z-score of public attention, news attention, strategic organizational attention, and Twitter attention. I do not difference[8] the time series as they all pass ADF tests, suggesting that they contain no unit roots.

I created a dummy variable representing events as an exogenous control variable in the VAR model. To detect events, I apply the approach used in Thorson and Wang (2019). The assumption of this approach is that events may prompt bouts of intense attention and cause outliers in attention metrics across media platforms. For each time series data (i.e., public attention, Twitter attention, news attention, and strategic organizational attention), I first calculate an outlier that is more than 1.5 interquartile ranges for each year and set it as a threshold. Then, I identify all days that contain a value that surpass the threshold values. I define these days as the attention spike days that associated to a climate change events. Based on the quantile method, I detect 162 outliers from Twitter, 58 from press releases data, 92 from news coverage data, 0 outlier from Google Trends Index. The dummy variable marks the total 312 outliers as “1” and others as “0”.

The Granger causality test and Impulse Response Function (IRF) are two follow-up analysis to interpret VAR model (Shellman, 2004). The Granger causality test examines whether a variable is better predicted by its own lags and another variable’s lags (Freeman, 1983; Granger, 1969). For example, for two time series data x and y, x Granger causes y if the past values of x and y together can betterer predict the current value of y than just using the past value of y alone. Referring the way of visualizing the results of Granger causality test (Peng et al.,

[8] Differencing a time series means using its value at time t to minus its value at time t-n ($1<n<t-1$).

2017), I build a network, where each endogenous variable is a node, each significant bivariate Granger causality relation is an edge, and the direction of the Granger causality test is also the direction of each edge. Following by Granger causality tests, I performed simulations based on Impulse Response Function (IRF). IRF detects the dynamic polarity and the magnitude of the impact from one variable to the other, thereby allowing me to understand the feedback across each variable over time (Shellman, 2004).

Temporal Aggregation

RQ2 asks whether the pairwise temporal relations tested in H_1 and H_2 maintain as the same with different temporal aggregations. To answer this question, I conducted two VAR models. One is based on the daily aggregated time series data, the other based on monthly aggregated time series. Based on the information criteria (AIC and HQIC), I chose 8 as the number of lags for the daily model and 2 as the number of lags for the monthly model.

Results

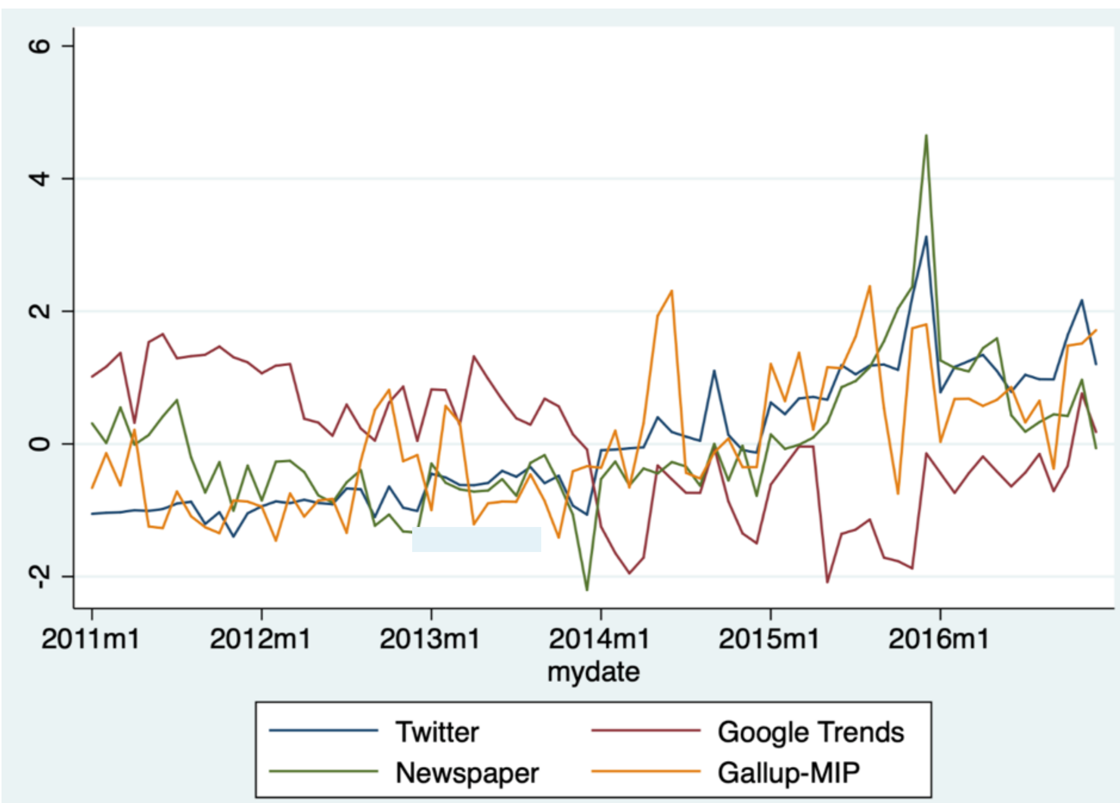
Comparison of Climate Change Attention

To recap, RQ1 asks the difference between public attention and public opinion, news attention, social media attention, in terms of its intensity, sustainability, volatility, and cyclical nature. An overview of the long-term monthly patterns (see Figure 4) reveals that each form of attention has a distinctive pattern. Public attention, measured by people's search behavior, shows a decreasing trend, whereas others reveal an increasing trend. The spikes of each source sometimes converged. For example, at the end of 2014, 2015, and 2016, each time series data seems to increase sharply. However, other times, these patterns across data sources vary a lot.

As for the cyclical nature of attention (see Figure 5), after decomposing each time series, I found that Twitter, Google Trends Index, and news appear to have slightly different seasonality. The seasonality pattern of public attention is consistent with Mellon's (2014) study in which he identified a sudden drop in public attention to climate change every end of December and January. This finding suggests that over a longitudinal perspective, rather than following Downs' (1972) issue attention cycle, public attention mostly follows cultural rituals (mostly the western holiday season). The news and Twitter attention also contain a sudden drop in every end of December and January, but they also see an annual peak around early December. This links to the annual United Nations Climate Change conference during every late November or early December from 2011–2016. In comparison, public opinion data shows no seasonality over time.

Figure 4

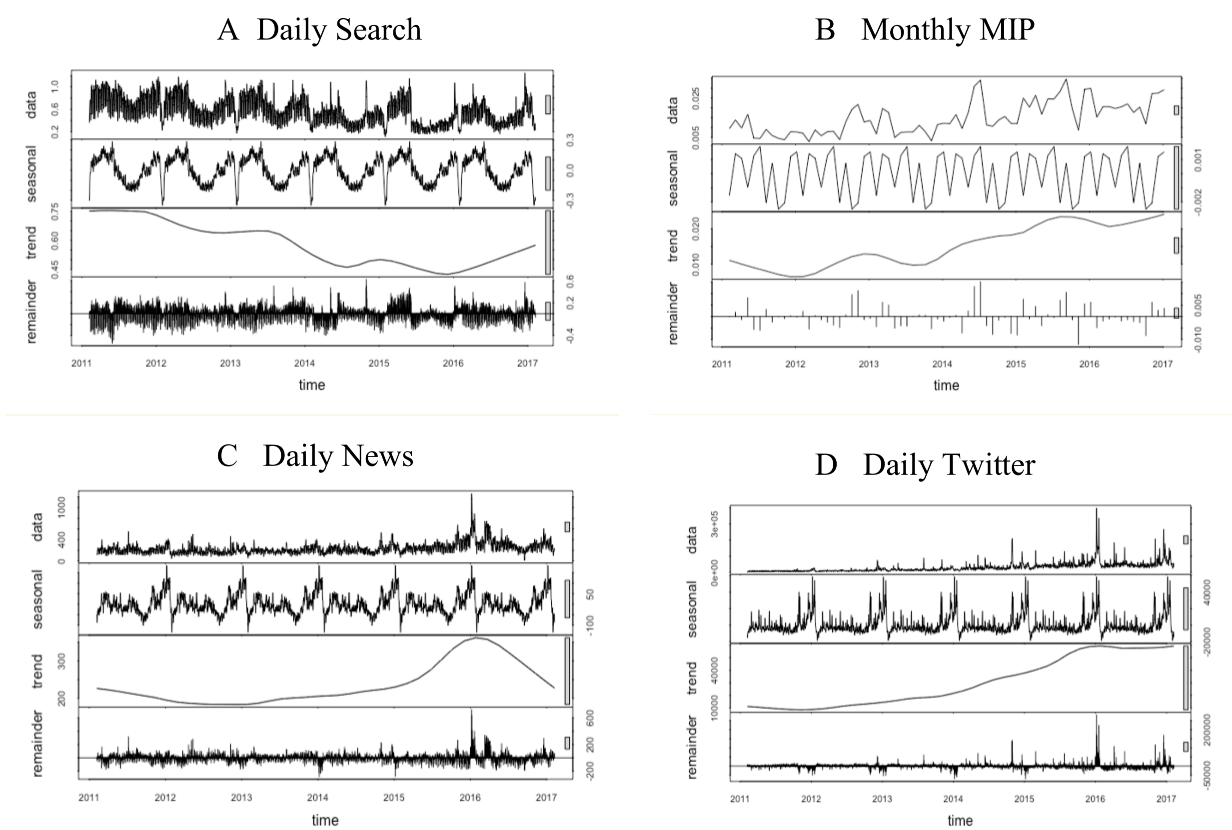
Comparison of Monthly Climate Change Attention from Multiple Sources, 2011–2016



Note: The metrics from each source are rescaled into Z-score.

Figure 5

Seasonality from Google Trends Index, Twitter, News and Public Opinion Poll, 2011–2016



Notes: The figure shows the results of STL decomposition from each time series data. The first row of each Figure is the raw data. The second row shows the decomposed patterns of seasonality. The third row shows the trend. The last row is the remainders after decomposing seasonality and trends. This figure includes only MIP monthly data because only the monthly MIP data is available to this dissertation study via the library database of Michigan State University.

As for sustainability, Table 2 presents the results. The memory of daily public attention, news, and Twitter all barely last more than a week. Specifically, Public attention has a 5-day memory span. News attention has a 7-day memory, and Twitter has a 6-day memory. Public opinion does not have daily-level data points, but it also does not last more than a month. Although the results do not show much difference across these forms of attention, each of them shows distinctive sustainability.

In term of the intensity and volatility, Table 2 presents the results. Overall, the results indicate that daily Twitter attention to climate change has the highest volatility, meaning users' attention to this issue on Twitter fluctuates quickly day by day and month by month. Twitter also has the highest intensity of daily attention, meaning that over this period, Twitter tend to raise extreme levels of attention about climate change events. But news has the slightly higher intensity at the monthly level. This is perhaps because news attention is also slightly more sustainable than Twitter attention. Gallup's monthly public opinion poll has the least volatility and intensity among all the different media types, meaning that public opinion about climate change is much more stable than the public's attention to it. Compared to news and Twitter, Google Trends data have the least volatility, both at daily and monthly levels. In other words, the results suggest that public attention to climate change is less stable than the public's opinion of it, but more stable than that the attention from news attention and Twitter attention.

Table 2

A Comparison of Intensity, Sustainability, and Volatility of Climate Change Attention, 2011–2016

	Intensity	Sustainability	Volatility
<u>*Daily*</u>			
Twitter	12.6	6 days	0.82
Newspaper	9.7	7 days	0.39
Google Trends	2.9	5 days	0.15
<u>*Monthly*</u>			
Twitter	3.3	< 1 month	0.75
News	4.7	< 1 month	0.27
Google Trends	2.3	< 1 month	0.14
Gallup	1.7	< 1 month	0.008

Notes: The intensity is the max value of the Z-score of each time series. The volatility is the Coefficient of variation of each time series. The Coefficient of variation is calculated by the diving standard deviation by the mean of each raw time series data. The sustainability is the number of significant lagged variables in the ADF test formula. The Gallup opinion poll is monthly only, it does not have a daily value.

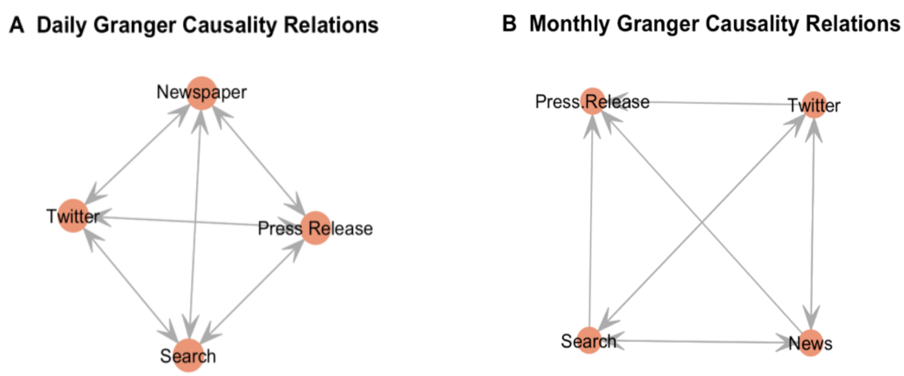
In sum, the findings from this section shows the answer to RQ1 is that public attention is different from public opinion, Twitter attention, and news attention in terms of volatility, intensity, and cyclical natures. Public attention is less volatile and less intensive than Twitter and news attention, but it is more unstable than public opinion. The cycle of public attention follows west cultural ritual, the Twitter and news attention follows both west cultural rituals and United Nation's annual international conference. Public opinion does not show clear cycles.

Pairwise Temporal Relations

As a recap, H_1 and H_2 test the pairwise relationship among public attention, news attention, strategic organizational attention and Twitter attention forms of attention over time. and RQ2 asks about whether these temporal relationships remained as the same at monthly and daily level of temporal aggregation. Figure 6 is a visualization of a directional network that shows the results of Granger causality tests. H_1 hypothesized attention from news media, social media, and strategic organizational actors predict public attention to climate change over time. Figure 6A supports this hypothesis and shows that news, social media, and strategic organizational attention all Granger cause public attention at daily level. More than that, public attention *also* Granger causes news, social media, and strategic organizational attention. H_2 hypothesized attention from news media, social media, and strategic organizational actors mutually predict each other over time. Figure 6A support this hypothesis and shows that they Granger cause each other at the daily level. This reflects the intertwining and interdependent relationships across media. Figure 6B reveals that the answer to RQ2 is that variation exists in the temporal relationships at different time aggregation. The mutual correspondence between news, Twitter, and public attention still holds at the monthly time scale. However, strategic organizational attention does not predict but only follows other forms of attention. This suggests that the function of press releases from the strategic organization is not robust in building agenda in the long run, counter to agenda building theory.

Figure 6

Visualization of the Granger Causality Test Results



Notes: Each node represents the exogenous variables in the VAR model. A link between two nodes indicates that one variable Granger causes the other. The direction of the edge indicates which node precedes the other. See Appendix B for the numeric results of these Granger Causality tests.

An IRF simulation shows the dynamic polarity of the intermedia relationships (see Figure 7). Each row shows that when a shock (one-unit increase of standard deviation) is introduced to a source, how the source and other sources respond to this shock. For example, the four trend lines in Row 1 show that when a shock happens in the news, it responds, as do press releases, public attention, and Twitter posts. The results show four highlights. First, a one-unit standard deviation increases in Twitter posts also positively increases search behavior by about 0.25 standard deviation on the next day. A one-unit standard deviation increase in Twitter posts about the climate issue produces an immediate upward shift in news coverage close to 0.5 standard deviation on the next day. A one-unit standard deviation increase in Twitter posts creates a small positive increase in organizational attention (press releases) by about 0.1 standard deviation, in the first two days. In contrast, news triggers less changes in other forms of attention. A one-unit standard deviation increase in news attention produces almost no immediate changes in Twitter or public attention. But news produces a delayed increase in press release after two days.

Figure 7

The Simulation of the Impulse Response Function with 95% Confidence Intervals

A. Daily Analysis

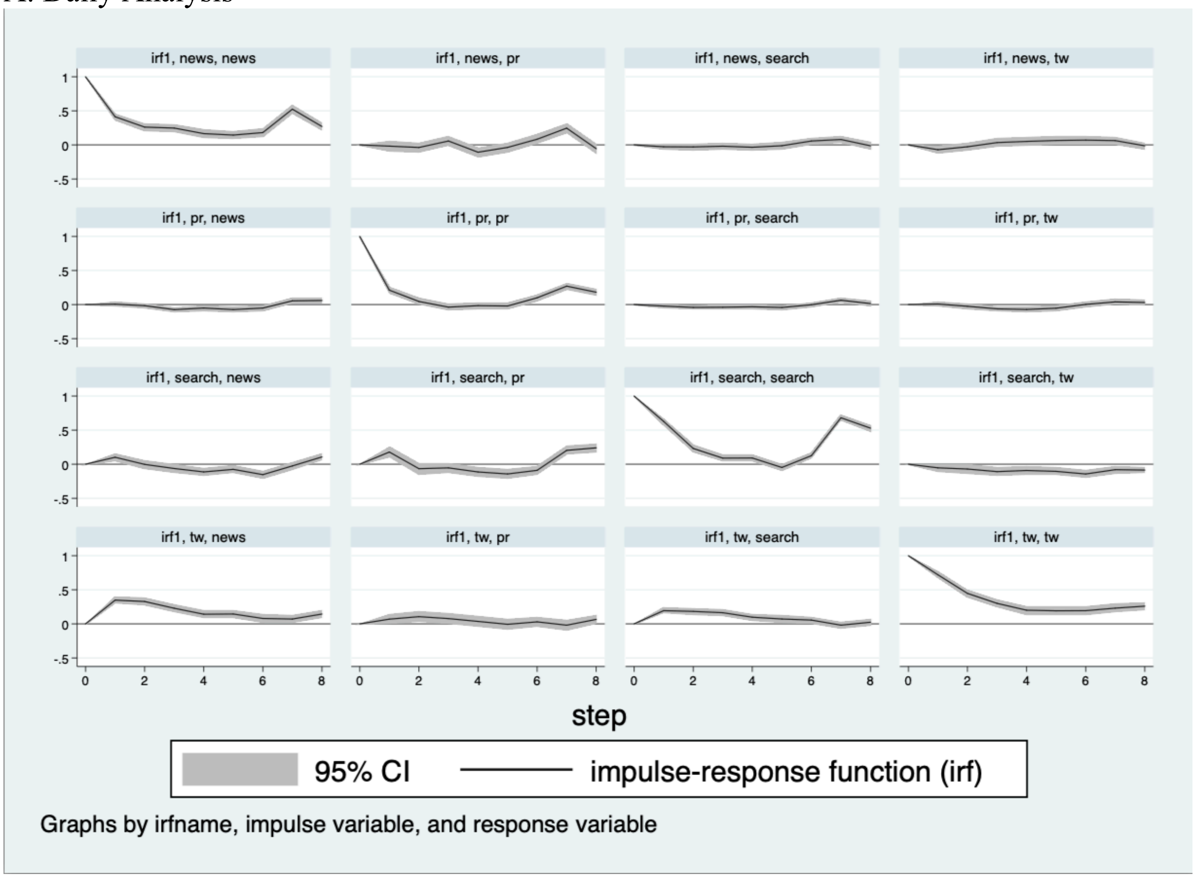
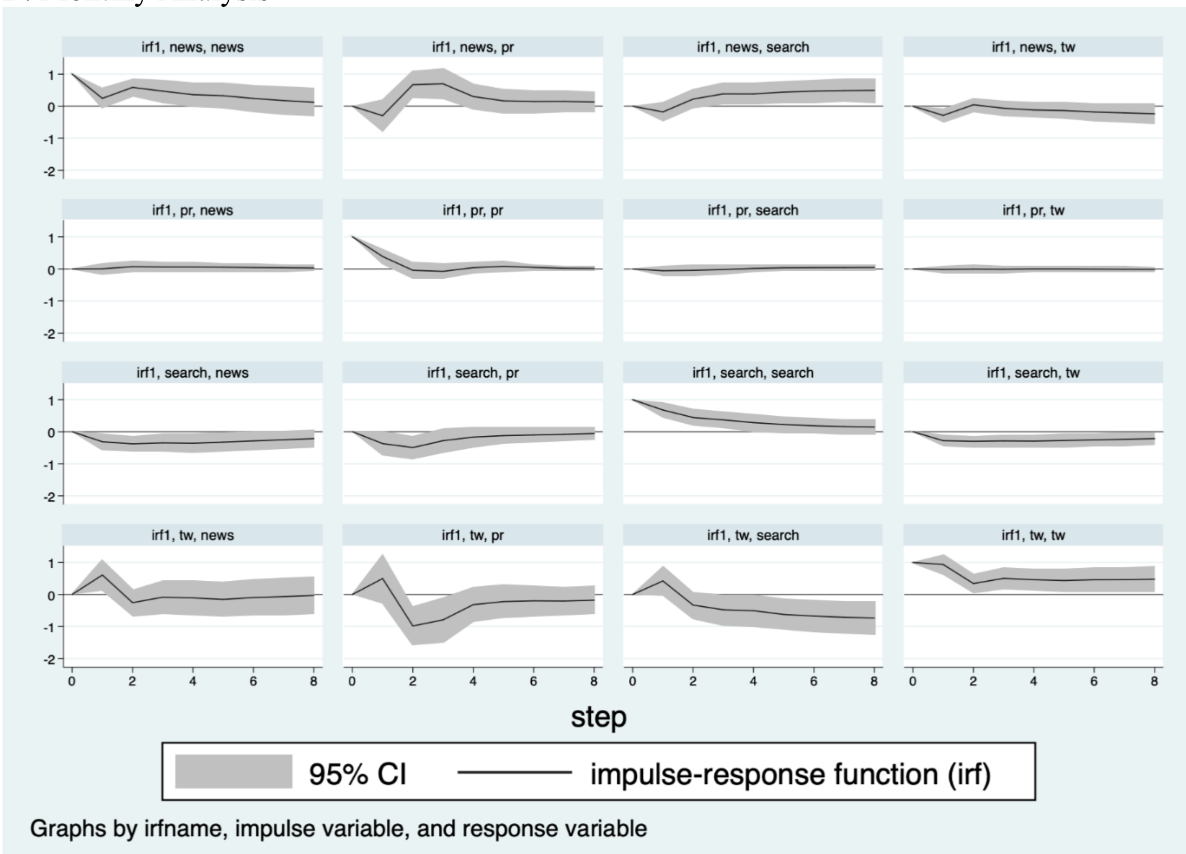


Figure 7 (cont'd)

B. Monthly Analysis



Notes: The *y*-axis shows the changes in the standard deviation of attention from one platform. A positive value means positive impact from the shock. The *x*-axis shows the time period of daily (Figure 7A) or monthly (Figure 7B).

Second, the IRF at the monthly level indicates that Twitter sometimes produces faster and stronger responses to other forms of attention than those produced by news, but the impact from news coverage tends to last longer than Twitter attention. As illustrated in Figure 7B, a one-unit standard deviation increase in Twitter also produces a slight increase in public attention, but this too decays within the month. In contrast, news produces a small, gradual increase in public attention by the end of the first month, which lasts approximately a full month. Twitter also produces an immediate upward shift in news attention by almost half of one standard deviation by the first month, but this increase disappears soon afterward. In comparison, a one-unit standard deviation increase in news produces slight decrease in Twitter attention to climate change for the first month, and then slightly increase in the second month, and then this effect decays. Twitter produces a transient increase in strategic organizational attention during the first month, whereas news produces a lagged increase in the second month and then lasts for two months.

Third, the Granger causality tests at both levels indicate that public attention predicts attention from news and strategic organizations, but the IRF analysis shows the impact size is limited. At the daily level, a one-unit standard deviation increase in public attention produces only a slight increase in press releases and news the subsequent day, but its impact quickly decays. At the monthly level, A one-unit standard deviation increase daily public attention produces declines in news and press release. This finding suggests that the two forms of organizational attention do not always linearly respond to public attention. News and other organizations still have their own agenda, particularly in the long run. This perhaps also suggests a kind of diminishing effects of the public attention on organizational attention.

Lastly, the IRF analysis shows that public attention also has limited impact on Twitter attention. At the daily level, a shock from public attention produces negative changes on Twitter. At the monthly level, a shock from public attention produces a negative change in Twitter attention. A possible explanation is that public attention represents attention both climate change activists and climate change doubters, whereas public opinion represents only the people who show concern about environmental issues, including climate change. As for the findings that public attention triggers less Twitter attention, this seemingly counterintuitive result may be related to the political polarization of climate change on social media. Social media maintains or perhaps reinforces the polarization in mass media. Cody et al., (2015) found that most Twitter users who tweet about climate change events are climate change activists rather than climate change deniers. The climate change activists also spent more time seeking information about the causes and impact of, as well as possible solutions for climate change than their more doubtful counterparts (Jang & Hart, 2015).

In sum, findings from this section shows that H_1 and H_2 are supported. At a daily time scale level of analysis, news, Twitter, and strategic organizational attention predict public attention, although in return, public attention also predicts news, Twitter, and strategic organizational attention. News, Twitter, and strategic organizational attention mutually predict each other. At the month-by-month time scale, strategic organizational attention does not predict and only follow other forms of attention. Thus, the answer to RQ3 is that there exists variance at different temporal aggregation.

But beyond that, there is much variance behind the dichotomous question about whether a form of attention predict the other. For example, the dynamic polarity and the magnitude of news attention and Twitter attention show a lot of heterogeneity. Twitter is a fast platform that produces large but transient changes in public attention, whereas news is a slow platform that produces accumulated change in public attention month by month.

Discussion

This chapter treats public attention as a distinctive analysis category. It has accomplished two goals: First, I examined how public attention is different from public opinion, news attention, and Twitter attention. Using Google Trends to measure public attention to climate change, I have compared the four attributes of public attention, public opinion, news attention, and Twitter attention. Second, to tease out causal relationships among the different types of attention. I have examined temporal relationships among public attention, news attention, Twitter attention, and strategic organizational attention. The findings from this chapter shows two key insights.

First, public attention, when measured by Google Trends Index is empirically distinct from news attention, social media attention, and public opinion in terms of intensity, volatility, sustainability, and cyclical changes. In general, previous studies held that any form of attention is short-lived and highly volatile in the contemporary hybrid media system. However, these findings provide evidence of the contrary, revealing heterogeneity among different media outlets' attention patterns regarding climate change. For instance, public attention is less volatile than Twitter and news attention. Twitter, in contrast, may be more volatile because users post about a variety of topics every day, thereby creating an highly competitive attention market (Anderegg & Goldsmith, 2014; Holmberg & Hellsten, 2016; Lorenz-Spreen et al., 2019). In terms of the cyclical natures, Downs's (1972) issue attention cycle suggests that the patterns of attention correlate with the development of an issue or event. My longitudinal observations, however, also show that public attention has seasonality pattern, following cultural rituals at the end of December and early January—the holiday season widely celebrated in Western countries. The cycles in Twitter and news attention follows cultural rituals and also the annual United Nation's annual conferences around every December. In contrast, the cycle of public opinion does not follow the same pattern with public attention. The findings also show that public attention is empirically different from public opinion. Public attention is less stable than public opinion, which affirms Newig (2004) and Ripberger's (2011) claims about the distinct temporal attributes of these two constructs. Public attention and public opinion are also different in terms of cyclical changes. This relation is sensible, given the different concepts these two terms represent.

Second, the analysis shows the temporal dynamics among attention from public attention, news, Twitter, and strategic organizations are different at the daily level and monthly level. The temporal relationships between these forms of attention shift depending on the unit of aggregation. That is, different temporal units of aggregation (daily versus monthly) yield different "causal" relationships. These shifts in findings does not mean that the results are invalid or contradictory. Rather, these temporal analyses examine two types of relations—one is a temporal relation between these media types during the span of day and the other is a cumulative temporal relation between these media across the span of a month.

My findings suggest that these sources of climate change attention mutually influence each other day by day, but underlying the interdependence among different forms of attention, the role of Twitter and news to influence public attention is contingent on time. Twitter is a fast platform that produces the most intensive, volatile, and responsive attention to climate change events. It also has a larger impact size on daily public attention. This finding echoes Weeks and Southwell (2010), who found that Google search queries and news coverage about political rumors were correlated by day. Also, this finding shows that Twitter can mobilize large scale public attention soon in the immediate aftermath of a climate change event, but its impact may be short-lived compared to other types of media. In this case, Twitter attention is volatile and short-lived, just as many other empirical studies have shown (An et al., 2014; Holmberg & Hellsten, 2016; Su & Borah, 2019a; Thorson & Wang, 2019).

In comparison, this study finds that news is a slow platform that produces large changes in public attention that are observable on a monthly scale. It is possible that this is because newspaper still have a (relatively) slow publication cycle. Previous findings from public opinion studies show that it takes about 1–2 months for news attention to potentially drive changes in public opinion. Similarly, my findings show it takes news about two months to generate changes in public attention. Taken all together, Twitter plays the role of shaping public attention in creating strong but transient changes in public attention, whereas news plays a role in influencing public attention in the long term.

This chapter contributes to the methods of analyzing the dynamics of public attention in two ways. First, the results of people's Google search queries suggest that each search term ("climate change" and "global warming") may be attributed to different groups of people. Whereas the search term "climate change," is positively correlated with Gallop's public opinion poll data, in which respondents note that the environment is the most important problem facing the United States, the search index, "global warming," is unrelated to this poll data. These differences could be explained by the polarization of public opinion to climate change. Jang and Hart (2015) analyzed tweets including the words "climate change" and "global warming" for 2 years. Based on this analysis, they found that climate change doubters and people from Republican-leaning states in the United States tend to use the term "global warming" more than "climate change", and their tweets often questioned climate change. Meanwhile, climate change activists and people from Democratic-leaning states used "climate change" more frequently in their tweets (Jang & Hart, 2015). Thus, future studies should operationalize public attention as a neutral measure, and they should include both "climate change" and "global warming" in their analyses to reduce sampling bias.

Second, this chapter suggests a way of extending theoretical contribution by replicating time series analysis based on multiple levels of time aggregation and then analyze the source of different results. Previous studies often just chose one time aggregation for time series analysis (Wells et al., 2019), but findings from this chapter show that this approach may limit our understanding of time effects. Analysis based on the lower level (e.g., hourly, daily) examines the temporal relations between different time series variables. Analysis based on the higher level (e.g., monthly, annually) neutralizes the real-time dynamics but allows us to see how many temporal interactions may produce cumulative effects over a long time. A few previous studies using time series have also identified the value of using different time compression. For example, Shellman (2004) conducted VAR models with time series data aggregated by days, months, and quarters and found that the quarter unit of aggregation masked relations between two variables exposed when using daily aggregated time series data and shift the polarity of influence. To study intermedia transmission of climate change attention, it is necessary to zoom in the time series analysis with smaller temporal units, because levels of attention change quickly in today's hybrid media system.

The study does not come without limitations. First, in this chapter, I have also discussed the technical strength and weakness of using Google Trends Index as a measurement of public attention. However, Google Trends Index is only an alternative method. It is not the perfect and the only way to measure public attention. Conceptually, I treat public attention as a valuable resource in the media system. I define public attention as the shared awareness expressed by a collection of ordinary people on any given issue. In terms of being a valuable resource, Google Trends data is a strong indicator of public attention to a social issue by monitoring its evolution of public attention over time. The data function like a stock market index that capture the constantly changing market expectation to a firm. But in terms of being a shared awareness from ordinary people, Google Trends data is not a perfect indicator. It is likely that not only ordinary people but also organizations conduct searches of climate change on Google. It is also likely that an ordinary people repeatedly conduct searches related to climate change, or an ordinary people express his/her attention to the climate change issue but never search about it. The anonymity of Google Search Trends makes it challenging to identify whether a search behavior comes from ordinary people or organizations, nor to tell the volume of unique ordinary user who search about climate change. Future studies may consider how to combine different methods to measure public attention. For example, scholars can integrate Google Trends with survey data. Researchers can sample participants who are representative of the ordinary people and ask questions such as what social issue they pay attention to, whether they have searched about the issue online, and what search queries they have used.

Second, based on the findings, Twitter is the most impactful platform to study the temporal dynamics of public attention, but the design of this study cannot not provide more information about users on Twitter. This chapter does not consider the presence of news media on Twitter. Previous studies have shown that the news media are major influencers on Twitter (see., e.g. Kirilenko et al., 2015; Pearce et al., 2014). News media, together with other traditional gatekeeper such as political actors and other major advocacy organizations, mutually shape the diffusion of climate change attention on Twitter in micro dynamics. This chapter also did not consider the micro dynamics among different types of actors on Twitter. It can only speak to the temporal dynamics of the climate change attention between different media platforms. As a follow up, the empirical studies in Chapter 4 and 5 focus on Twitter attention and disaggregate Twitter users into different sets of actors to understand how they dynamically spread attention to climate change across different media.

In conclusion, despite the limitations, this chapter extends the current literature by clarifying our understanding of the conceptualization of public attention, its temporal relationship with other forms of attention, and the analytic methods to deal with the dynamics in examining public attention. The findings in this chapter suggests that public attention is a distinctive category and should be measured independently from news attention, twitter attention, and public opinion. Twitter is an important platform that produces dramatic changes in Twitter attention and a large response from public attention and news attention. In contrast, news generates sustained changes in public attention in the long run. Strategic organizational attention rarely produces much changes from other forms of attention in both short term and long term. Given the presence of traditional gatekeepers like news on Twitter, future studies should consider identifying the organizational actors and examine who triggers the spikes of climate change attention on Twitter and expands the attention to other media platforms.

CHAPTER 4: A METHOD TO AUTOMATICALLY CLASSIFY TWITTER USERS

The goal of this chapter is to introduce a machine learning approach to classify Twitter users into the following five mutually exclusive categories: individual actors, news actors, political actors, advocacy actors, and other organizational actors. Most of the existing literature on intermedia agenda setting (e.g., Jang et al., 2017) and intermedia attention contagion (e.g., Nahon et al., 2013) treats Twitter as aggregated attention or as a proxy for public attention. In this chapter, I argue that these studies fall short because in addition to ordinary people on Twitter, many organizations, such as news media outlets, politicians, and advocacy groups, also use Twitter and, in so doing, help shape the public's opinions, awareness, and attention of climate change. To theorize how public attention evolves within today's intermedia ecology (Harder, Sevenans, & Van Aelst, 2017b; Jones-Jang et al., 2020), one must observe the patterns of public attention not only across varied media platforms but also across different sets of actors. However, considering the thousands of Twitter users and tweets on climate change, it is methodologically challenging to accurately classify these users into distinct sets of actors at scale.

To facilitate this categorization process, I designed and validated an automated classification method that integrates supervised machine learning, crowdsourced human coding, and a dictionary approach. Specifically, using this automated method, I effectively classified 288,829 Twitter users across four major climate change events into their respective actor categories.

This chapter extends the current literature based on intermedia attention patterns in two ways. First, it demonstrates the necessity of disaggregating Twitter users when attempting to understand the intermedia diffusion of climate change attention, because organizational Twitter users may be an influential source of information that affects public attention, particularly with respect to climate change. Several existing studies have shown the dynamic interrelations between individual and institutional actors on Twitter (Kwon et al., 2018; McGregor et al., 2017; Segerberg & Bennett, 2011) and have suggested that the dynamics within a media platform could influence issue attention within the overall media ecology (Lörcher & Neverla, 2015b). To build off this initial work, future studies on the intermedia diffusion of public attention and intermedia agenda setting should empirically take into account the complexities and diversity of Twitter users. The second contribution of this chapter responds to this particular need of intermedia agenda setting research. Specifically, this chapter offers an effective methodological approach for automatically classifying Twitter users, which improves the usability of crowdsourcing services and existing multiclass classification approaches.

In what follows, I first discuss the prior studies about intermedia diffusion of attention and their limitations. Then, I explain the rationales and existing approaches for disaggregating Twitter users. Afterward, I introduce an automatic approach to classifying such users. Specifically, I offer a supervised machine learning (SML) model and a dictionary-based classification that can differentiate news actors, political actors, advocacy groups, and other organizations from ordinary individual Twitter users. I introduce the challenges, solutions and the process of building the SML model, particularly when using crowdsourcing. Finally, I test my proposed approach by classifying Twitter users across four high attention climate change related events on this platform.

Prior Studies about Intermedia Diffusion of Attention

Several prior studies focus on intermedia diffusion of attention use an intermedia agenda setting approach. The central focus of intermedia agenda setting research is to understand the transfer of attention across different media platforms (Harder et al., 2017). However, most of these studies have treated Twitter or social media, more generally, as a proxy for public attention and contrasted this form of attention with news media attention. For example, to examine the distinct dynamics of public attention in social media versus traditional media, Neumann et al. (2014) created an aggregated measure of public attention, combining attention across Twitter, blogs, and online forums, and contrasted it against online news attention. Most recently, Jones-Jang et al. (2020) studied the contagion of public attention surrounding climate change across different media over time. They found that online news reports predicted the volume of tweets over the time. Then, they concluded a top-down pattern of intermedia influence—that is, they proposed that elite news media attention influences ordinary users in a one-way direction.

Although these studies highlight the importance of contextualizing public attention across multiple media platforms, they only compare flows of attention in online news versus aggregated patterns of attention on Twitter. These studies overlook, for example, the role of news media actors on Twitter as well as the role their communication behaviors may play in shaping the public's attention to climate change. Thus, these studies only minimally help explain what may prompt changes in public attention in today's intermedia ecology. To understand what may influence public attention in the present hybrid media system, scholars need to disaggregate Twitter users. In this way, researchers may examine which set of actors initiate or drive public attention to climate change and which actors follow these forerunners' lead (Jones-Jang et al., 2020).

Why Disaggregate Twitter Users?

There are three primary reasons ungirding the need to disaggregate Twitter users when studying the diffusion of public attention in a hybrid media system. First, Twitter users include both organizations and ordinary individuals—groups with distinct capacities in affecting public attention. By comparing 34,000 Twitter accounts, representing a mix of organizational users and individual users, McCorriston et al. (2015) found that organizational users have significantly more followers and friends than individual users. Accordingly, organizational users are more likely to be sources of climate change information than individuals. Demonstrating this point, tracking 42 million Twitter users and 5 billion tweets for 223 days, Wu et al. (2011) found that organizational users, such as news media outlets and other organizations, were responsible for 50% of all retweets, even though these users represented only 0.05% of the overall Twitter population. They also found that organizational users and individual users had different communication behaviors, with individuals generating far more content, on average, than organizations. Although individuals produced more content, organizational users have more followers and thus more likely to drive the conversations about climate change than individual Twitter users.

Second, Twitter serves as a network stitching mechanism (Bennett & Segerberg, 2012), which connects a variety of organizational and individual actors together during a climate change event. Among organizational actors are news media, political actors, and advocacy groups—the three types of actors critical in influencing public attention, as shown in the previous chapter (Brulle et al., 2012). Twitter is a tool and object for news, political, and advocacy actors, which enables them to strategically communicate with ordinary individual Twitter users and generate more attention that aligns with their respective agendas (McGregor et al., 2017). As suggested in Chapter 3, organizational actors' presence and interactive communication with the individual users could increase Twitter attention to climate change. In another example, Segerberg and Bennett (2011) analyzed the connectivity and the sources of tweets during the 15th United

Nations Conference of the Parties on Climate Change (COP-15) in 2009. They found that advocacy groups used Twitter as a major platform for mobilizing public attention to the climate change issue. Therefore, treating Twitter as an aggregate form of attention overlooks the impact of different types of actors within the space on the dynamics of public attention.

Third, Twitter connects different types of actors in an underlying network structure, which can challenge the power of established institutions (i.e., traditional gatekeepers) in directing the public's attention toward (and away from) specific issue areas (González-Bailón et al., 2010). Agenda setting, agenda building, and gatekeeping theories suggest that a small group of organizations control most sources of information and create a "structural bias that limit the breadth and agility of the public attentiveness" (Neuman, 2016, p.208). As for the climate change issue, a few studies have shown that small group of organizational actors shape climate change attention on Twitter (see e.g., Kirilenko & Stepchenkova, 2014; Veltri & Atanasova, 2017), but the network mechanisms from the information diffusion theories contend that the structures of information diffusion networks determine who holds the power to direct Twitter attention. For example, by bridging otherwise unconnected networks together, weak ties in diffusion networks often enable large-scale contagions of information (Watts & Strogatz, 1998). The two-step flow (Katz, 1957) suggests that opinion leaders bridge elite media and ordinary people and, in turn, amplify media attention to wider audiences. The theory of weak ties (Watts & Strogatz, 1998) and two-step flow theory (Katz, 1957) maintain that network structures give power to ordinary people and, thereby, enabling them to challenge organizational Twitter users' control over public attention.

Supporting these canonical studies, many recent network analyses have shown that the structure of social networks can increase the impact of regular people in information diffusion.

Observing 622 million tweets, Goel et al. (2016) found that diffusion can happen via a broadcasting model (from one to many users), a viral model (from person to person), or through a combination of both models. Across all kinds of events, they found that online diffusion was often a combination of both models. Watts and Dodds (2007) found that a large cascade of influence often links to interpersonal communication between individual users rather than from the direct communication from news and elites to individuals. The interpersonal communication from a critical mass of easily influenced individuals spurred a chain reaction that spread attention to more individuals. Other empirical studies have found that online communication networks tend to show a core and periphery structure (e.g., Barberá et al., 2015; Gomez-Rodriguez et al., 2010; Liu et al., 2015). For example, based on four retweet networks related to protests in different countries, Barberá et al. (2015) found that the actors at the core of these networks were typically the main source of attention, while actors at the periphery—often individual users—were far less impactful in the diffusion of information across Twitter. Instead, peripheral actors tended follow whatever information core actors shared (or spread) on Twitter (Barberá et al., 2015). However, because actors in the periphery substantially outnumber those at the core of these networks, the impact of peripheral actors' aggregated attention compared to that of those few core actors (Barberá et al., 2015). In sum, these findings suggest that a user's identity as either a traditional gatekeeper, an organization, or ordinary individual matters relatively little in the diffusion of information; rather what matters is one's position in the network structure. Specifically, the limited number of users at the core disproportionately control the public's attention on Twitter.

The above theories and empirical findings connect to the lasting debates on the conceptualization of public attention discussed in Chapter 2. As aforementioned, agenda setting and agenda building theories emphasize the strength of organizations, particularly traditional gatekeepers, in shaping public attention even with digital media. Meanwhile, the network mechanisms in the information diffusion studies show the important role of ordinary users in influencing traditional gatekeepers and in contributing to the diffusion of public attention. To extend the theorization of public attention and examine the respective capacity of different actors in spreading awareness about climate change, it is necessary to differentiate traditional gatekeeping actors from individual actors on Twitter. Considering this need, I ask: Among all Twitter users involved in popular climate change related events, what share represent news, political, and advocacy actors? Toward answering this question, I discuss existing approaches to disaggregating Twitter users.

Ways of Disaggregating Twitter Users

Since my focus in this present study is on news, political, and advocacy actors' role in shaping public attention to climate change, I review communication studies that specifically categorize Twitter users into these three types of users. Based on this review, existing research that explores the dynamics of different actors on Twitter use two main approaches to creating and labeling typologies of Twitter users. Specifically, to disaggregate and categorize Twitter users, researchers typically apply either (a) an indexing approach, (b) a human coding approach.

Disaggregating Twitter Users with an Indexing Approach

First, some researchers apply an indexing approach. In this case, researchers compile an initial list of specific Twitter accounts, representing different types of users. For example, Bailo and Vromen (2016) analyzed the tweets of a predetermined list of users, which including news media, unions, politics, and social movement organizations, to examine the dynamics of Twitter attention during protest events in Australia. Similarly, wanting to analyze the tweets pertaining the 2014 U.S. senatorial campaign and, in particular, different actors' contributions to this conversation, McGregor et al. (2017) manually compiled a list of Twitter users' representing news media and political elites and then collected and analyzed these two sets of actors' respective tweets. In short, when using an indexing approach, scholars, in effect, preeminently disaggregate Twitter users, as they determine upfront a list of users in each respective category and then pull the corresponding data of interest to them from this preset list of accounts.

As with all methodological decisions, the indexing approach has its strengths and limitations. In terms of the former, the index approach providers scholars more control over the quality of account classification. Since Twitter contains a variety of types of users, the index approach can effectively avoid the false positive case. For example, avoiding categorizing a non-political account as a political one. However, a major challenge of this approach is that an a priori list of actors is likely not comprehensive or representative of all Twitter users contributing to an issue area. This approach presumes that the researchers know all the possible users within each relevant actor category. Inevitably, they will exclude people or actors relevant to their analyses. Considering the global nature of an issue such as climate change, large swaths of actors across many different countries tweet about this issue and/or engage in related Twitter discussions and events.

Disaggregating Twitter Users with Human Coding

Another way that researchers approach disaggregating Twitter users is to rely on human coders to classify users. For example, Stier et al. (2018) used PageRank centrality[9] to filter the top 500 most important nodes (i.e., Twitter users) from a retweet network about climate change,

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[9] PageRank is a way to evaluates the centrality of a node in a network.

and then recruited a team of people to code these users as either political elites, news media, industry, celebrity, nonprofits, or individual activists.

Again, this specific approach as both its benefits and drawbacks. As far as benefits of this disaggregation methods, human coders can identify more categories of Twitter users than a machine can. For example, Thorson and Wang (2019) coded 1,371 users consistently involved in key climate change moments on Twitter from 2011–2015 into 12 categories: individual users, advocacy groups, online only media, advocacy media, journalists, environment professionals, educators/scientists, mainstream media, political/governmental actors, celebrities, religious entities, and other. In contrast, a more automated approach may not provide the same level of nuance. That is, a computer, perhaps, may not be able to consistently distinguish environmental professionals from educators/scientists. Assuming the coding teams maintains a reasonable agreement and intercoder reliability rate, this approach provides quality control to the noise on Twitter and removal of bots. However, at the same time, a group of human coders cannot feasibly classify a large-scale number of users, and indeed, typically, human-coded typologies focus on only a small subset of important accounts. Consequently, this approach would not allow a researcher to test important hypotheses, such as some of those about the effect of the core and periphery structure of information diffusion networks on, for example, public attention to climate change. For instance, a human-coded approach to disaggregating Twitter users would likely be unfeasible if attempting to test if peripheral users are equally important for attention diffusion compared to core users—there are simply too many users to code. In short, while human coders can add nuance to typologies, this approach is time-consuming.

Disaggregating Twitter Users with an Automatic Classification Method

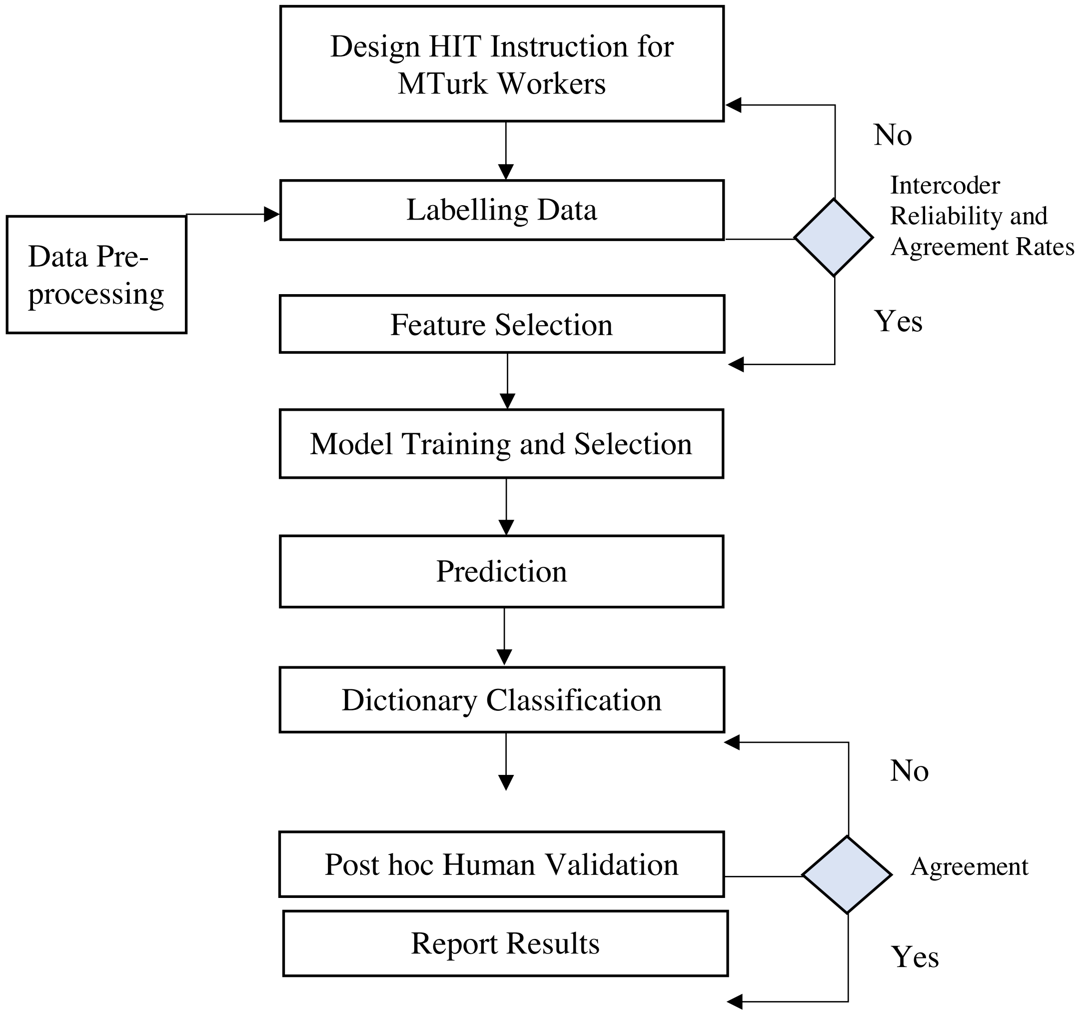
In general, SML approaches train algorithms based on labelled data and then use the algorithm to predict new data. In this section, I summarize the supervised machine learning (SML) approach that I take to classify users and then explain why I use this approach, as well as its challenges and possible solutions.

I first used SML to classify Twitter users into organizational and individual users. I trained the SML model using the crowdsourcing platform, Mechanical Turk's (MTurk) labelling data. Then, I built and applied a dictionary to the SML model, enabling it to detect and distinguish news actors, political actors, and advocacy actors. After integrating this dictionary, I validated my results by calculating the model's agreement rate based on random sampling inspection. Although presented a linear, step-by-step process, developing this automated method was an iterative process, with much back and forth until I was able to ensure the reliability of the model's results. Figure 8 provides a summary of this multistep process, which I explain in more detail in the following sections.

I used SML because it can automatically classify a large number of Twitter accounts. In general, SML includes three steps. Researchers first construct a high-quality dataset labeled by human coders. Second, researchers split user data into two groups—one subset for training purposes and the other one for testing. Using the training data, the researchers develop a few machine learning models based on features of the selected data, which they then evaluate with the testing data. Lastly, researchers apply the tested algorithm to classify users from new data. In other words, researchers do not code every new Twitter user, but use the SML model to predict which kind of actor each new user is within their dataset.

Figure 8

Summary of the Automatic Classification Steps



The SML classification approach is not new; computer scientists have long used it in their research about Twitter user classification (see e.g.,Efthimion et al., 2018; McCorriston et al., 2015; Pennacchiotti & Popescu, 2011; Purohit & Chan, 2017; Wang et al., 2019; Wood-Doughty et al., 2018). For example, McCorriston et al. (2015) used an SML model to identify organizations from 34,000 randomly collected Twitter accounts. Wood-Doughty et al., (2018) used convolutional neural network (CNN, an SML model) to identify organizational users from

Twitter. Wang and colleagues used deep neural learning (a SML model) to estimate gender, age, and status (organization or individual account) of Twitter users (Wang et al., 2019). Recently, communication scholars have also started using SML models. For example, Kwon et al. (2018) used a SML model to differentiate organizational accounts from a dataset of 7,000 users previously manually labelled.

To further identify news, political actors, and advocacy group actors, I used a dictionary method. Although multi-class categorization, which classifies users into three or more than three categories, is potentially possible, I built a dictionary for two reasons. First, SML models do not work well in identifying small categories because there are not enough relevant samples within labelling data (Burscher et al., 2014). In fact, because of this shortcoming, most existing SML studies have just focused on classifying Twitter accounts into only two categories—organizational users and individual users. In this case, I wanted to disaggregate the users into three types of actors (i.e., political actors, news media, and advocacy groups). However, the share of each type of actor within the labelling data was substantially different, meaning some categories were quite small. For example, based on a preliminary review, political actors seemed to only represent a small percentage of all organizational users within this data, meaning my SML model would likely be somewhat ineffective at reliably classifying the appropriate users as political actors. Second, in my pilot study in which I designed and tested the labelling of MTurk workers, I found that my SML model yielded low quality results, specifically with the identification of political actors—a point I return to in later section.

Challenges of the Supervised Machine Learning Approach

There are two main challenges with using SML models. First is the quality of labeling data. The quality of labeling data is proportional to its cost, such that affordable options are often low quality, whereas more expensive data tends to be of higher quality. Crowdsourcing platforms, such as MTurk, are cost effective. However, without a robust quality control system in place, labeling data available through MTurk is unlikely to produce precise results for a coding schema with multiple categories. Because of the low compensation for most Human Intelligence Tasks (HITs) (with workers earning a mere $0.05 per HIT), many workers rush through HITs using the least amount of effort of possible. Problematically, typologizing a user into more categories requires more complicated HIT instructions, and the added effort such HITs pose introduces potential quality issues in MTurk users responses. Even binary labelling tasks, such as dividing users into organizations or individuals, requires some instructions, and researchers must employ an evaluation system to examine the quality of their work (Morales, Borondo, Losada, & Benito, n.d.). Therefore, to maintain high quality work, I simplified the data labelling process and tested various instructions descriptions to find a clear set of instructions for this HIT. In the labelling data section, I explain the quality control process in more detail.

The second challenge of creating generalizable SML models is the representativeness of the labelling data. McCorriston et al. (2015) made their SML model publicly available, including their high-quality labeled data of 20,273 active Twitter accounts (active, at least, before 2012). However, they trained the model based on randomly sampled users in general, rather than from a specific event. Thus, this labeled data may not be generalizable to a larger Twitter user base involved in the climate change issue on this platform, meaning this data may not be accurately predicting different types of actors tweeted in climate change events. Kwon et al. (2018) found that SML models trained with random data were far less accurate in predicting the types of users involved in specific issue on Twitter than SML models training with data of the same type of event. As such, to ensure the generalization of my labeling data, I used Twitter data related to climate change events, not randomly selected data.

The final challenge is the quantity of organizational accounts in the labelling data. As shown by McCorriston et al. (2015), a random sample data of 20,000 accounts contained only 9.4% of organizational users. And, Wu et al. (2011) found that among 42 million Twitter users they observed, only about 0.05% of them were news media outlets, celebrities, or organizational users. With potentially few organizational users, or samples, in the training data, the SML model will be unable to produce accurate results. To mitigate this issue, I increased the ratio of accounts, making it such that the data was more likely to include more organizational users than likely expected within the Twitter population. Again, I return to this point when I describe the process of developing my SML model.

Data Collection and Preparation

I used full firehose Twitter data—the same data used in several existing empirical studies (i.e., Thorson & Wang, 2019; Wang, Yang, & Thorson, 2019). The data contains tweets including the keyword "climate" published during high-volume attention events related to climate change. To detect these high-volume attention events, researchers plotted the volume of tweets from 2012–2015 from Crimson Hexagon[10] using "climate change" as the keyword. Thorson and Wang (2019) used the quantile approach[11] to determine the time windows for each of the four events. Then, they purchased the full set of tweets published during these time windows that contained the keyword "climate" from Sifter[12].

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[10] Crimson Hexagon is a consumer insights company that keeps publicly available posts and documents from social media such as Twitter, Instagram, Facebook, blogs, forums and news.
[11] Quantile approach: The outliers are identified annually from each source, using the formula (3rd Quantile-1st quantile) *1.5 + 3rd quantile. They marked days with values larger than the set threshold as outliers.
[12] Sifter used to be an authorized reseller of Twitter data.

I selected four events that happened between November, 2014 and November, 2015. Specifically, the four events are: (1) the U.S.–China Climate Agreement (258,043 tweets, 115,040 unique users), which happened during the G20 Summit held November 12–14, 2014. The political actors released an announcement about the joint efforts that China and U.S. would make in combating climae change (The White House, 2014); (2) Earth Day in 2015 (200,003 tweets, 106,036 unique users). It is an annual event globally celebrated on April 22 to demonstrate support for environmental protection. First celebrated in 1970, it now includes events coordinated globally by the Earth Day Network in more than 193 countries (Earth Day, n.d.); (3) The People's Climate Movement in 2015 (178,766 tweets, 102,302 unique users). The People's Climate March took place on October 14, 2015 as a climate change social activist event organized by a coalition of advocacy organizations in the US (People's Climate Movement, n.d.); (4) Obama on Facebook (137,873 tweets, 80,918 unique users). On November 9, 2015, President Barack launched his personal Facebook page and mentioned climate change; the event, Obama on Facebook, refers to this act (Schulman, 2015). Table 3 summarizes the Twitter event data.

According to Thorson and Wang (2019), these four events belong to different event categories. The U.S.–China Climate Agreement belongs to the international climate-related conference or summit. Earth Day and the People's Climate Movement are both climate change activism campaigns. Obama on Twitter is a political event related to politicians or have political implications.

I did not analyze all the Twitter users, since the goal of disaggregating Twitter accounts is to better understand the transmission of attention within and beyond Twitter, I focused on the retweet network for each event. Retweet networks provide a framework to understand how attention flows from one actor to another (Barberá et al., 2015). In other words, retweet networks represent a kind of social network that connects people who express and spread climate change attention. More granularly, in a retweet network, each user is a node. Each tie links a user, or node, who originally posted a tweet with users who retweeted it.

Table 3

Description of Twitter Event Data

Event	U.S.–China Climate Agreement	The Earth Day 2015	People's Climate Movement	Obama on Facebook
Event Date	November 12, 2014	April 22, 2015	October 14, 2015	November 9, 2015
Timeframe	November 12–14, 2014	April 21–23 in 2015	October 13–14 in 2015	November 9–10, 2015
Tweets	258,043	200,003	178,766	137,873
Unique Users	115,040	106,036	83,486	80,918
Event Description	The political actors released an announcement about the joint efforts that China and U.S. would make in combating climae change. It is a climate change-related summit.	An annual event globally celebrated on April 22 to demonstrate support for environmental protection.	A social activist event organized by a coalition of advocacy organizations in the US.	President Barack launched his personal Facebook page and mentioned climate change.

To build the four retweet networks, one for each of the four high-attention volume events, I used R. Specifically, I first selected all tweets including "RT@" or "via@." Then, I created a retweet network based on an edge list that included the Twitter handles of users who published a retweet and the handles of users who created the original tweet. The retweet network has directions—indegree and outdegree. The indegree of a user represents the frequency at which the user’s tweets were retweeted, and the outdegree of a user represents the frequency at which a user retweeted other users’ tweet. Table 4 provides a description of the number of unique users and retweets each of the four retweet networks.

With only the retweets, U.S.-China Agreement contain 80,918 unique users. The Earth Day contain 77,605 unique users. People’s Climate Movement data contain 73,178 unique users from. The Obama on Facebook contain 57,128 unique users. The final data from four events include a total of 288,829 unique users.

Table 4

Metrics of Retweet Networks for Climate Change Events, 2014–2015

Network	U.S.–China Agreement	Earth Day	People’s Movement	Obama on Facebook	Total
Nodes (users)	80,918	77,605	73,178	57,128	288,829
Degrees (retweets)	137,873	114,380	97,492	76,440	426,185

Notes: The table shows the number of unique users and retweets in the three event retweet networks.

Building the Proposed Automated Disaggregation Method

As a reminder, I propose an SML model as well as a dictionary to disaggregate Twitter users into distinct categories. To follow, I describe the multi-step process I undertook to develop the proposed SML model. I then discuss the process of creating the accompanying dictionary.

Building the Proposed Supervised Machine Learning Model

In general, the process of building SML models follows six steps. In the first five steps, I used a combined total of 7,219 users from the Earth Day event and the U.S.–China Climate Agreement event to build the SML model. In the last step, I used the developed SML model to predict the classification of Twitters users into their respective categories (i.e., political actors, news media, and advocacy groups) across all four events.

Step One: Data Pre-Processing. In this initial step, I had three main goals. The first goal was to sample data representative all climate change events, so as to later build a generalizable SML model. Toward this, I selected user data from the Earth Day event and the U.S.–China Climate Agreement retweet networks, because these two networks contained the most users among the four event-related retweet networks. The second goal was to include enough organizational accounts within the training data. In service of this goal, I filtered out users with less than five ties in their retweet network, assuming the majority of Twitter users who posted fewer than five retweets tend to be individual users. Since this is data is from 2014–2015, the third and last goal of this initial step was to remove defunct users—accounts no longer presently on Twitter. These inclusions of these now deactivated accounts would create noise for MTurkers and unnecessarily increase costs, because it will be meaningless and increasing the cost to make MTurkers to code accounts that no longer exist.

To identify these deactivated users, I used the rtweet R package and the user ID (a unique combination of numbers) of each user. Using this package, deactivated accounts had missing user IDs. About 81% of users in the Earth Day event and about 83% in the U.S.–China Climate Agreement event were still active Twitter accounts (see Table 5 for more details about the actives users in other event data). These numbers of deactivated accounts correspond with the results of a recent study. Attempting to update user data from 2012, Daouadi et al. (2018) likewise found that about 83% of Twitter accounts were still active at the time of his analysis some 5 years later.

Table 5

Active Twitter Users from Four Event Retweet Networks

Network	Obama on Facebook	US-China Announcement	Earth Day	People's Movement	All Events
% of active users	82%	83%	81%	78%	81%
Number of active users	13,760	23,438	21,732	21,448	80,378

Notes: This table checks the ratio of active users in the retweet network. Since the data points in the historic data were created by Twitter users in 2014/2015, around 20% total users became inactive users.

After removing these inactive users—which represented approximately 20% of the total dataset across these two events—the final dataset used to train the SML model included 4,867 users from the U.S.–China Climate Agreement and 2,370 users from the Earth Day event. Thus, I prepared a total of 7,237 accounts for human labeling. There are some overlapped accounts, but there were less than 1.5% accounts repeatedly show up in the two events. For more details about the overlapped users, please refer to Thorson and Wang (2019).

Step Two: Labeling Data. I employed MTurk workers to label each of the 7,237 users. Specifically, each MTurk worker read the provided instructions and received an URL link to each corresponding user's Twitter page. As mentioned earlier, a major challenge of this step is ensuring the quality of MTurk workers' labelling. Attempting to limit the number of instances of mislabeling, I hired only Master workers (workers who passed MTurk's Master's Qualification[13]) with a HITs' Approval Rate[14] above 95%. To further limit labeling issues, two separate MTurk workers labeled each account. I calculated intercoder reliability to validate the labelling results.

[13] According to Amazon, a Master Worker is a top Worker of the MTurk marketplace that has been granted the Mechanical Turk Masters Qualification. These Workers have consistently demonstrated a high degree of success in performing a wide range of HITs across a large number of Requesters.
[14] The Approval Rate is the rate that Requesters have approved HITs that Workers complete, according to Amazon.

To further improve labeling accuracy, I picked 500 Twitter accounts to test and optimize the instructions I provided to MTurk workers engaged in this process. At first, I used the instructions developed by Thorson and Wang (2019), which included 12 distinct categories, but the labeling results, using this schema, were poor. That is, MTurk workers mislabeled a substantial number of accounts. Given those unpromisingly results, I then used the coding instructions developed by Kwon et al. (2018), which included five categories (i.e., politicians, news media, professionals, groups/organizations, and other). Using these categories and their corresponding instructions likewise yielded low quality results. Specifically, MTurk workers were largely inaccurate in their coding of users as news media outlets and politicians. For example, they coded most governmental sectors outside the United States as "other," instead of labeling them as political actors. In short, when using this multi-categorical coding schemas, it seems that MTurk workers were rather inaccurate, frequently mislabeling users.

Finally, I used Purohit and Chan's (2017) HIT instructions, which explained to MTurk workers how to label accounts into the following four categories: (a) organizational accounts (which included celebrities, such as movie stars, famous musicians, and business tycoons), (b) organization-affiliated professional accounts, (c) individual accounts (ordinary users who does not indicate an affiliation to any specific organization or group), and (d) none. None refers to instances when the worker could not determine the categorical classification of the account or it the account appeared to be a bot[15]. The result showed better quality.

Given that fewer categories would likely increase the accuracy of labeling, I combined organizational accounts and organization-affiliated professional accounts into one category

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[15] A Twitter bot automatically perform activities such as tweeting, retweeting, following another account. Bot software controlled a bot account via Twitter API(Efthimion et al., 2018).

called “organizational accounts.” I also instructed MTurk workers to code non-affiliated individual accounts as “individual users,” and the noncategory as “none.” Then, after every round of labeling, I calculated the agreement and intercoder reliability rates. To avoid cases where the two coders both miscoded an account, I conducted a post-hoc verification, randomly selecting 200 accounts and calculating the two MTurk workers’ agreement rate—a process I describe in more detail under step six. Ultimately, I adjusted the instructions until the final intercoder reliability rate reached 0.77 (Cohen’s Kappa) and workers maintained an overall 96% agreement rate in their labeling of user accounts. Figure 9 provides the final set of instructions provided to for MTurk workers.

The data labeled by MTurk workers included 3,970 individual users, 3,178 organizational users, and 89 none users. I manually categorized the 288 accounts which MTurk workers did not agree upon as well as the 89 accounts classified within the “None” category. After manually reviewing the 89 users from the “none” category, I removed 18 accounts, representing a mix of bots and porn accounts, from the labeling data, because they did not post about climate change related tweets. However, I kept four bot accounts because they only tweeted about climate change news—“ClimateChange36,” “NewsClimate,” “climatechange_a,” and “Climatenews”—and consistently appeared across the sampling time windows. I included these four bots in the dictionary under the label, “news actor.” I did not use the tool, Botometer,[16] to systematically remove bots from the data, because this tool inaccurately estimates inactive accounts as bots. The final data for building the SML model contains 7,219 accounts.

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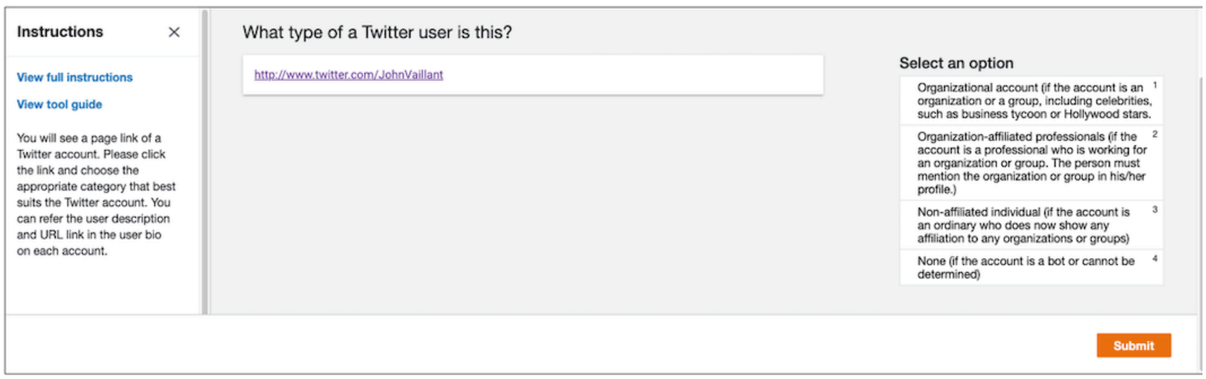
[16] Botometer estimates a Twitter account and gives a score indicating the likelihood that the account to be a bot. The estimation is based on the activities of a Twitter account.

Figure 9

An Example of a HIT Instruction for MTurk Workers



Step Three: Feature Selection. The next step was to select features. These features represent predictor variables that help SML models predict whether an account is an organizational or individual user. Existing computer science studies have used a variety of features, ranging from the content of user's tweets, user's profile photos, or user's bio descriptions. In general, they used three types of features or a combination of these three types of features to predict organizational Twitter users: user-profile features, content-based features, tweeting behavior features. User profile features are predictors such as the external URL revealed by an user in the Twitter profile, the number of posts, the number of friends, the number of favorites (see e.g., Kwon et al., 2018; Wang et al., 2019; Wood-Doughty et al., 2018). For example, Wang et al. (2019) applied user profile images and other text features to identify organizations and to estimate the gender and age of the Twitter user. Kwon et al. (2018) used lexicon features from the user's bio line to identify organizational accounts on Twitter. Wood-Doughty et al., (2018) predicted user type focused on the user profile on Twitter (URL in the user profile and the Twitter List created by a user). Content-based features are predictors that based on the lexicons of tweets (McCorriston et al., 2015; Oentaryo, Low, & Lim, 2015). For example, McCorriston et al. (2015) selected features of users' tweets, such as the frequently used terms and hashtags as well as a tweet's average character count. Oentaryo et al., (2015) used the word frequencies (normalized by term frequency-inverse document frequency) of tweets published by users they examined. Tweeting behavioral features include predictors that are based on the communication networks on Twitter, such as the number of times a user retweet, mention or reply to another user. For example, Alzahrani et al., (2018) used the centralities (degree centrality, PageRank centrality, K-core centrality) from retweet network, follower network and mention network for each user. Tweeting behavioral features also include predictors such as the average frequency of tweets per day/week/hour and the intervals between posts in seconds (Tavares et al., 2019; Tavares & Faisal, 2013). Majority of the existing studies often combine the three types of features (e.g., see A. Kim et al., 2017; S. Kim et al., 2019). For example, to identify individual Twitter users who Tweet about E-Cigarettes, Kim et al. combined user-profile features and tweets content features (A. Kim et al., 2017).

Among the array of different feature options, researchers have found that information from a user's profile is the most relevant predictor of whether a user is an organization or not. For instance, Daouadi et al. (2018) compared models developed using a non-exhaustive combinations of tweets content features, user profile features, and retweeting behavior features. Based on their analysis, they found that models based on information from users' profiles had a 91.4% accuracy rate. More specifically, the features included a user's: (a) number of followers and following; (b) the ratio of followers to following; (c) listed count (the number of times an user was added to a list by other users); (d) number of favorited tweets, (e) average number of post per day, and (f) total number of tweets.

Drawing on the previous studies using the user profile features (Daouadi et al., 2018; A. Kim et al., 2017; McCorriston et al., 2015; Purohit & Chan, 2017; Wood-Doughty et al., 2018), I used 12 features to train my SML algorithms to classify Twitter users into distinct actor categories. These features included a user's number of friends and followers, ratio between friends and followers, listed count, favorites counts, and average number tweets per day. Additionally, I included the average length of time since the creation of account, whether the account included external URLs in the bio line, and whether Twitter had verified the account. Also, pulling from another study focused on the real-time identification of organizational users (Karbasian et al., 2018), I built in an additional three lexicon features to improve the SML model; these included (a) the total number of characters used in user's bio line, (b) the sentiment score[17] of a user's bio, and (c) a binary variable, in which a value of "1" indicated that the user included an emoji(s) in their handle and a value of "0" if otherwise. To collect this user profile data[18], I used the R package rtweet. Appendix C provides a full description of these features.

Step Four: Model Training. I split the labelling data into training data and testing data. Specifically, I assigned 80% of the data to training and the remaining 20% for testing purposes. I applied several popular machine learning algorithms to train data, including Linear Discriminant Analysis, K Nearest Neighbors, Random Forests, and Support Vector Machine. After running these algorithms with the training data, the algorithms produce models comprised of parameters. For example, Random Forest algorithm results in a tree model with "if-then" statement based on specific values (cite the statistical learning text book).

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[17] I calculated the sentiment of a user's bio line using the R package sentiment.
[18] For full variables that Twitter opens to the public in metadata, please refer: https://developer.twitter.com/en/docs/tweets/data-dictionary/overview/user-object

Step Five: Model Validation, Selection, and Testing. I conducted 10-fold cross-validation to the training data to estimate the performance of each model on new data. In the 10-fold cross validation, the computer randomly split the training data into 10 equal-sized subgroups. For each of the 10 groups of samples, the computer assigned one group as testing data and the remaining 9 groups as training data. The computer then replicates this process 10 times and then calculates the average estimate. In short, this validation process helps estimate the performance of each model. Separately, I also applied these models to the testing data to evaluate their performance. Following Daouadi et al.'s (2018) example, I used four indicators to evaluate my proposed SML model: accuracy rate, F1 score, precision, and recall rate. As a note, I discuss this process in more depth in a later section. Table 6 shows the indicators that I used to evaluate SML models.

Table 6

Indicators of Supervised Machine Learning Model Performance

SML Model	LDA	CART	KNN	SVM	RF
Precision	87%	81%	80%	85%	84%
Accuracy	80%	80%	79%	81%	83%
Recall	72%	83%	82%	77%	83%
F1	79%	82%	81%	81%	84%

Notes: The table shows the criteria to evaluate the performance of five SML models.

Step Six: Prediction. I applied Random Forests—the best SML model identified in Step 5 and predicted the categorical classification of users across all four event-based retweet networks. Different from other SML models, Random Forests builds decision trees that make "if-then" decision based on the specific values of a set of predictors. Each time the model considers a split in a tree, it chooses a random sample of features from the full set of features. Then, it selects only one of those randomly sampled features (James, Witten, Hastie &

Tibshirani, 2013, p320). Table 7 shows the results. Based on the results from Random Forest, I selected all accounts for the dictionary classifier. The dictionary further distinguished news actors, political actors, and advocacy actors from one another.

Table 7

Classiciafion Rresults from SML from the Four Events

	U.S.–China Agreement 2014	Earth Day 2015	People's Movement 2015	Obama on Facebook 2015
Individual actors	64%	58%	58%	57%
Organizational actors	36%	42%	42%	43%

Building the Dictionary

As mentioned earlier, given limitations of SML models, I created a dictionary to identify and differentiate news actors, political actors, and advocacy actors. The main assumption of such dictionaries is that certain unique indicators from users' profiles can help disaggregate these three types of users. Accordingly, to build this dictionary, I followed Wu et al.'s (2011) method for identifying celebrities, media outlets, organizations, and bloggers on Twitter. Specifically, I reviewed the bio lines, usernames, and external URL links in user profiles across a few accounts in each of three respective actor categories (i.e., political actors, news actors, and advocacy actors)[19] from each of the four climate change-related events. As part of this work, I manually compiled a list of users, representing major advocacy organizations and non-profit organizations related to the climate change issue. I also conducted computer-assisted textual analysis to examine the lexicon features of the bio lines of each type of actor. Furthermore, I determined the term frequency (including bi-gram) and the tf-idf (the frequency and inverse document

[19] I referred this link to build the list
http://www.aag.org/cs/programs/interdisciplinary/climatechange/clearinghouse/organizations

frequency) of each user. The tf-idf is an information retrieval technique that indicates the importance of a word in a user's bio among particular type of users (Tahmasebi & Risse, 2017). Then, I hand-selected keywords as unique indicators of each category, meaning keywords should exclusively represent the target category and not overlap with any other categories. For example, for the news actors, I selected the keywords— "news," "journalist," and "correspondent"—since these were the most frequently used words in news actors' bio lines. I also found that the name of some news media outlets, such as Fox, appeared to have high tf-idf scores. Therefore, if a user's bio included such keywords, I set it such that the computer automatically coded the user as "news actor."

Although the description presented here reads rather straightforwardly, it bears noting that building this dictionary was an iterative process. I applied the dictionary to the organizational accounts identified by the SML model. After each dictionary classification, I randomly sampled 200 accounts from each set of actors and manually evaluated the results. I went through this process multiple times until I finally modified the dictionary in such a way that the accuracy rate of each set of categories was above 90%. Table 8 offers more detail about the unique indicators used for each category.

Table 8

Examples of Dictionary Keywords per Actor Category

Category	Example of Keywords
Advocacy	grassroot organizations, climate campaign, grassroot movements, in the profile description; grassroot organizations, climate campaign, grassroot movements, in the profile description; major climate change advocacy organizations and nonprofits, such as Sierra Club, Greenpeace, WWF; The major international organizations such as United Nations, OECD and UN's specialized agencies such as UNEP were categorized as advocacy actors too

Table 8 (cont'd)

News	news, reporters, journalist, correspondent, magazine, chief editor, and senior editor
Political	MP, Senator, Governor. The government sectors include external URL end with .gov, Attorney General, Prime Minister, Minister of, Embassy of, Ambassador to, USEmbassy, Mayor, POTUS
Individual actors	news junkie, news junky, news geek, reading news, not a fan of

Validating Results

To ensure the quality of the results from that automated disaggregation method and its accompanying dictionary, I validated the results from SML classification and dictionary classification. To follow, I describe the process that I used to validate results.

Validating the Supervised Machine Learning Model

Models based on the training data from two climate change events (i.e., Earth Day and U.S.–China Climate Agreement) had varied performance outcomes. Random Forest (Accuracy rate: 83%, Precision rate: 83%, Recall: 84%, and F1: 84%). SVM (Accuracy rate: 81%, Precision rate: 85%, Recall: 77%, and F1: 81%) had close performance to the Random Forest result. I selected Random Forest since it outperformed SVM across all four indicators. The performance of these models mirrors the results of other studies, likewise attempting to identify organizational users using a SML model based on user profile information (see e.g., Daouadi et al., 2018; Kwon et al., 2018; Purohit & Chan, 2017). Indeed, the accuracy rate (83%) of my SML model falls within the range set by previous studies (73.4%–95.3%).

I conducted an error analysis of the SML results and identified key sources of misclassification. For one, the SML model is poor at identifying organizational accounts with fewer than 1,000 followers, which have a similar number of followers and friends. For example, the SVM model tends to "think" some news professional accounts, a type of organizational account, are individual accounts because the two features just noted were integral to the classification of organizational users (See feature importance of the Random Tree Forest in Appendix D). Human coders, however, can easily tell that these accounts belong to news professionals by reading their bios, especially since many of them remarked in their bios that were journalists or somehow affiliated with a news media outlet. Second, the model also miscategorized organizational actors with no external URLs in their profiles and that also had few followers. For example, the model mistakenly coded Rwanda's former Minister of Natural Resources Vincent Biruta as individual account rather than as a political actor. Altogether, these error analyses point to the need to use the dictionary to accurately identify news actors, political actors, and advocacy actors across all the users derived from the SML model's predictions.

Validating the Dictionary

In attempting to validate the dictionary, I uncovered three sources of error in the disaggregation of Twitter user data. First is the negation before the determined set of indicator keywords. For example, if an individual actor wrote, "not a fan of Governor…" in their profile, the dictionary read the keyword "Governor" and, subsequently, classified the user as a political actor. As a solution, I added the negation condition "not a fan of …" into the dictionary. If a user profile contains the negation condition, the account will be coded to "individual actors". Another source of error in the dictionary was the context of the keywords. For example, the dictionary classified users whose external URL included ".gov" as political actors, because that indicates a governmental website. Using this rule, the dictionary detected various political accounts, such as NASA, Whitehouse, StateDept (the U.S. Department of State), MIBIndia (Ministry of Information and Broadcasting, Government of India), and several U.S. embassies. However, this rule also produced errors when considering some individual actors. For instance, some individual users, particularly people presumably aligned with the U.S. conservative party, included URLs ending in ".gov" in their profiles. As a solution, I hierarchically adjusted the execution of the rules, meaning I first ran general rules, such as inspecting whether an external URL ended with ".gov;" assuming they did, I coded the accounts as "political actors." Then, I ran an additional set of specific rules, such as inspecting whether a specific URL link (like https://www.greatagain.gov/) appeared in the coded accounts. If a user put this link in the profile, I adjusted the categorization of this accounts from "political actors" to "individual actors."

The third major source of error stemmed from initially only including keywords written in English. Although the majority of organizational users' bios were English, a few political accounts have bios in French. For example, French embassies often wrote their bios in French. Part of the user profile of the French embassy in Sweden reads, "Ambassade de France en Suède" instead of as "Embassy of France in Sweden." To address this issue, I added the keywords—"Embassy," "Ambassador," and "Consulate General"—in French to the dictionary. Although I also detected German, Spanish, and Russian in the user bios, majority of them existed in the individual users. I did not find other languages systematically generate the similar errors to other organizational accounts.

Post Hoc Manual Validation

The SML and dictionary classification typologized 288,829 users across the four events into five categories: news actors, political actors, advocacy actors, other organizational users, individual actors. I randomly selected 200 accounts from each event to validate the accuracy of these five categories. As shown in Table 9, the agreement rate range for political actors was from 94%– 99%. For news actors, the rate ranged from 91.5%–98%. For advocacy actors, it was from 95.5%–98%, and for other organizational actors, the rate fluctuated from 92%–95%. Most consistently accurate was the classification of individual actors, which hovered consistently around 99% across all four events. These rates suggest that my proposed SLM model coupled with the dictionary effectively differentiated users into their respective target categories.

Table 9

Agreement Rates in Post Hoc Human Validation

Event	U.S.–China Agreement	Earth Day	People's Climate Movement	Obama on Facebook
Political actor	99%	99%	94%	99%
News actor	98%	95%	98%	91.5%
Advocacy actor	95.5%	98.5%	97%	98%
Other organization	95%	92%	93%	92%
Individual actors	99%	99.5%	99%	99%

Notes: The agreement rate is calculated by using the number of wrongly coded actors divided by total actors.

Results

In terms of the distribution of each user category, there was not a great deal of variance across the four events (see Table 10). News actors represented 5%–8% of the total number of accounts across the four events. This category contained not only the official accounts of traditional news media outlets, such as *BBC*, *The Guardian*, *MSNBC*, and *The New Yorker*, but also major online news organizations, such as *Huffington Post* and *Buzzmedia*. This category also included more niche news media outlets focused on environmental issues and/or partisan politics, such as the *Red State* and *Mother Jones*. The dictionary also detected a variety of news professionals, including journalists, TV anchors, and commentators from traditional news media outlets, as well as citizen journalists and independent investigative journalists.

Table 10

The Proportion of Each Type of Users from the Four events

	U.S.–China Agreement	Earth Day	People's Movement	Obama on Facebook
Individual actors	64%	59%	57%	56%
News actors	5%	7%	8%	8%
Political actors	1%	1%	1%	1%
Advocacy actors	1%	1%	1%	2%
Other organizational actors	11%	12%	9%	12%
Account no longer exist	19%	20%	24%	21%
Total	100%	100%	100%	100%

Notes: The ratio is calculated by using the number of a user type divided by all the users who retweeted.

Political actors accounted for about 1% of all the included Twitter accounts. The dictionary detected not only government leaders and officials all over the world, politicians (e.g., Canadian Prime Minister Justin Trudeau, Indian Prime Minister Narendra Modi, and Former Australian Prime Minister Kevin Rudd), but also political actors across varied governmental levels (i.e., local, national, and international) and agencies, such as the NASA and the diplomatic accounts.

Advocacy actors accounted for about 1–2% of the data. Most of these accounts represented key environmental advocacy organizations, including major national nonprofits, international NGOs. This group of users also included grassroots climate change organizations, climate change campaign accounts, and professionals affiliated with these varied organizations and campaigns. For example, earthhourgy is a specific account dedicated to the Earth Day campaign.

Other organizational actors represent about 9%–12% of all accounts across the four events. These actors included celebrities, educational institutions, companies (e.g., General

Motors, Shell Oil Company, Safeguard), climate change scientists, and professionals affiliated with a wide range of organizations. This category also includes some partisan-identified organizations. For example, Appsame described themselves as, “a conservative political marketing firm helping to bring America back to its greatness.”

Lastly, comprising the largest single category of actors, individual users represented 57%–64% of all accounts across the four events. Individual actors included both climate change supporters and climate change doubters. In terms of the latter, many of these individual actors described themselves as “conservative” and/or as “Christian;” many also referred to themselves as a “patriot” or as a “Republican.”

Discussion

To recap, I used Random Forest to differentiate organizational actors from individual actors on Twitter. Using 7,237 labelling user data points, my proposed SML model performed well, realizing an 83% agreement rate. I then built a dictionary to identify news actors, political actors, and advocacy actors, achieving an agreement rate over 90%. I applied this approach to classify 288,829 users across the four climate change-related events into five categories: news actors, political actors, advocacy actors, other organizational actors, and individual actors. In brief, based on my success in disaggregating Twitter users into their respective categories, my proposed automatic classification method, which combines machine learning, crowd workers, and a dictionary, is an effective approach. Indeed, given the overall accuracy of this automated method, others should consider using it to classify Twitter users for future intermedia agenda setting research.

Through developing this automated method, I shed light on how to improve classification results in a cost-effective manner. More specifically, I offer three main insights. My first takeaway pertains to the importance of controlling the quality of crowdsourcing human labelling. When crowdsourcing the labeling of data, scholars need to (a) build in a quality control system that filters out workers with low quality work performance, (b) simplify the HITs, and (c) clarify HIT instructions. The second key insights relate to the dictionary. Dictionaries based on lexicon features can help identify political, advocacy, and news actors. However, when constructing such dictionaries, researchers must consider the context of the lexicon and multilingual users. As a third point, to maintain the generalizability of a SML model, it seems that scholars do not need to train the model for every event data. Instead, training a model based on the labelling data from two events is likely sufficient, allowing you to effectively predict the classification of users across other similarly related events. This echoes Kwon et al.'s (2018) work, who found that models based on news events of a similar topic perform well in predicting users' types from other similar events.

The findings also show that Twitter is a hybrid ecology that involves both organizations and individual actors, which presents three major implications in terms of building theories to explain the diffusion of attention across media. First, as mentioned in Chapter 3, Twitter could be an important place to raise public attention to climate change because it provides more sources of information and supports mass media in spreading climate change information (Tandoc & Eng, 2017; Schäfer & Schlichting, 2014). As shown in the four events included in this chapter, a wide range of actors, including the traditional gatekeepers (news, political elites, and large advocacy organizations) of climate change information and the individual actors were involved in a large retweet network. By sharing climate change information via retweet, these actors contributed to spikes in climate change attention on Twitter. Among organizational actors, there were also many grassroots advocacy groups, climate change activist groups, online news media outlets, companies, and organization-affiliated professionals. They represented organizations, but these users still likely generate informal person-to-person communication with individual actors.

Second, the findings revealed that many individual actors were partisan identifiers and climate change doubters, which supports the discussion presented in Chapter 3 about the politicized and polarized nature of the climate change issue. Polarization and disagreement on climate change are rampant on Twitter (An et al., 2014; Cody, Reagan, Mitchell, Dodds, & Danforth, 2015). By analyzing 1.5 million tweets related to the climate change issue over approximately a 6-year period (i.e., September 2008– July 2014), Cody et al. (2015) found that climate change events predominantly generated attention from climate change activists rather than climate change doubters. In different study, after conducting social network analysis of 590,608 tweets from 179,180 unique users, Williams et al. (2015) found that most of the time, Twitter users only communicated with like-minded others. However, future studies should explore whether or how the polarization of this issue influences the diffusion of public attention surrounding it within and across different types of media.

Third, the findings revealed the existence of news bots that spread climate change information. Given a politicized and polarized issue like climate change, how many other types of bots exist within networks of climate change discussion Twitter? What are the sources of these bots? Do these bots represent the views of particular institutions? If so, which ones and what effects do these bots pose of the diffusion of information and attention to climate change? To what extent might these bots reinforce the politicized and polarized nature of this issue? Future researchers should take some of the questions up in their work.

Although this chapter lays the methodological foundation needed for the next chapter, it does not come without limitations. First, the historic data from Twitter events provides a valuable archive of all the full users who expressed attention to the climate change events. However, an average of 19% users (around 54,877 users) no longer existed on Twitter. The inaccessibility of these users' information produces missing information, which limits my analyses of how information spread through Twitter. Second, although I have removed the porn accounts, I did not systematically filter out bots given the limitations of current bot detection tools. The third limitation is the features selection and my SML modeling techniques. Although I used a two-step approach to identify user types, using only metadata from user profiles, it is also possible to conduct a multi-task machine learning process using more relevant features. For example, Wang et al. (2019) created a multimodal deep learning algorithm that jointly classified Twitter users by gender, age group, and organizational/individual status. In future studies, communication scholars could collaborate with computer scientists to develop such a robust methodological innovation. It will also be valuable to build a universally generalizable model, which can apply to more issues besides climate change.

Despite of these limitations, this chapter still extends the current literature about the intermedia flows of attention in two ways. First, the evolution of public attention happens as climate change attention spread across media. Thus, it is necessary to disaggregate Twitter users to understand the intermedia flows of attention. Further, this chapter provides a methodological contribution with my proposed automated classification approach, which effectively differentiates news actors, political actors, advocacy actors, and other organizational actors from individual actors attentive to climate change. To understand the diffusion of public attention in a hybrid media system, however, two follow-up questions are relevant. Which types of actors contribute to spikes of climate change attention on Twitter over the time? Which type of actors on Twitter will predict public attention and other forms of attention outside Twitter? This methodological step in this chapter sets the stage for the empirical analysis carried out in Chapter 5, which pursues these very questions.

CHAPTER 5: THE INTERMEDIA DIFFUSION OF CLIMATE CHANGE ATTENTION IN DIFFERENT EVENTS

The goal of this chapter is to understand the diffusion of attention within the contemporary hybrid media system, particularly the spread of attention *within* and *beyond* Twitter surrounding several recent climate change-related events. One of the overriding challenges to studying this phenomenon is to sort out the intertwining, interdependent, and ever-changing relationships between and among an array of actors across multiple different media platforms (i.e., news media, social media, etc.). Indeed, existing studies have struggled to fully overcome this challenge. As noted in previous chapters, most existing information diffusion studies only focus on the micro-level dynamics between different actors on Twitter (see e.g., Kirilenko & Stepchenkova, 2014; Williams et al., 2015), while intermedia agenda studies tend to only emphasize the transfer of attention between media platforms and outlets, such as between news media and Twitter, and treat Twitter attention as a proxy for public attention (see e.g., Jones-Jang et al., 2020). Furthermore, few studies on climate change attention have considered how the context of particular events might shape patterns and the process in the diffusion of attention, even though Down's (1972) classic issue attention model suggests that context may, in fact, play a role in the spread of public attention. Existing studies have also not fully explained or theorized the heterogeneity in the evolution of public attention that scholars have found in different events, although climate change events have distinctive patterns and diffusion processes of attention.

Facing the limitations of existing literature, and having applied the method for disaggregating Twitter actors described in Chapter 4, this chapter focuses on three guiding questions: (a) Which types of actors shape the flows of climate change attention *within* Twitter over time? (b) How does climate change attention on platforms *outside* Twitter and climate change attention within Twitter respond to each other? (c) How much will different event contexts change the patterns found in (a) and (b)? To answer these questions, the empirical analysis in this chapter combines an intermedia agenda setting approach and an information diffusion approach to compare the diffusion of climate change attention on Twitter surrounding three key climate events in 2015: Earth Day, People's Climate Movement, and Obama's climate change-focused post on Facebook. Based on the classification results from Chapter 4, I examine the static and dynamic roles of five different types of actors (i.e., individuals, political entities, news media, advocacy groups, and other organizational actors) as (1) the sources of attention (original tweet creation) and (2) as attention spreaders in retweet networks. Then, using Google Trends data as public attention measurement and using the volume of online news coverage as a measure of news attention, I further analyze how retweeting activities by each type of actors *within* Twitter may interconnect with the public attention and online news attention *outside* Twitter. I replicated the same process of analysis to the three events.

As predicted by traditional agenda setting theories, I find that organizational actors (i.e., news, political, advocacy, and other organizational actors) still serve as the main source of attention within Twitter; however, these actors do not fully explain all the patterns in the diffusion of climate change attention within and beyond Twitter. Instead, I found that interpersonal communication on Twitter among individual actors and traditional gatekeepers (e.g. news, political actors, large advocacy groups) also helps explain these patterns. Indeed, as predicted by Nahon's network gatekeeping theory (2008), the gatekeeping role on Twitter (as a source or spreader of attention) is constantly shifting between organizational actors and individual actors over time. Further, to sustain Twitter attention and spread attention to other media platforms requires the integrated efforts of all types of actors. In the data, I observed moments that consistent integrate and synchronize attention from all types of actors on Twitter—and show that this consistent synchronization appears to be related to overall volume of attention to an event.

The findings contribute to the existing literature in two ways. First, the heterogeneity in the patterns of attention and the changing relations between each type of actors across media between the three events in the findings invites new theoretical opportunities to understand the diffusion of attention in the contemporary hybrid media system (as I outline in the final chapter of this dissertation). Second, this work provides evidence of the importance of considering the context in which events take place as well as the dynamism of the gatekeeper role in the study of attention diffusion within and beyond Twitter.

In that follows, I first briefly summarize studies on the role of traditional gatekeepers and individual actors in the diffusion of climate change attention on Twitter—a reminder of the literature I reviewed more deeply in Chapters 3 and 4. Then, I outline some of the main limitations within existing theoretical and empirical scholarship on intermedia diffusion of climate change attention. Then I discuss the importance of studying and theorizing the changing relationships between different actors across media in different event contexts, where the patterns and the processes of attention diffusion processes are distinct. Finally, I present the empirical analysis and results.

The Diffusion of Climate Change Attention on Twitter

In this section, I briefly reiterate the roles of each type of actors in the diffusion of climate change attention within Twitter. Specifically, I focus on two types of roles important to the diffusion of climate change attention on Twitter—sources and spreaders. *Sources* refer to those who publish original tweets and being retweeted by other users, while *spreaders* refer to those who retweet the original tweets. The sources of tweets are the seeds to a retweet network (Goel et al., 2015). Retweeting is an effective way to spread information (Kwak et al., 2010). Retweeting also increases the visibility of tweets and increases the likelihood that more users will share it (Lin et al., 2014). Moreover, retweeting creates a stream of messages that allow individuals to be "peripherally aware "of " without directly participating" (Boyd et al., 2010, p.1).

Based on the networked gatekeeping theory (Nahon, 2008), actors' roles may change over time; that is, sometimes, actors may fulfill the role of sources, and other times, they may serve the role of spreaders. Traditional gatekeeping theory assumes that mass media shape public attention by information control; it determines what to present and what to withhold to the public (Shoemaker, 1991). However, communications in the hybrid media system combine mass communication and interpersonal communication (Welles & González-Bailón, 2020). Thus, the extent to which traditional gatekeepers continue to control the spread of information and shape public attention has changed. In response, Barzilai-Nahon (2008) proposed network gatekeeping theory, which broadens the concept of gatekeeping as a networked process that controls information "as it moves in and out of gates" (Barzilai-Nahon, 2008, p. 1496). The theory also holds that it is impossible to identify a clear "gate" given the dynamism of network structures and the wide adoption of information technologies among the public (Barzilai-Nahon, 2008, p. 1496). Relatedly, Barzilai-Nahon maintained that the roles of *gatekeeper* and *gated* were in constant flux, switching back and forth between traditional gatekeepers and individual actors. In this process, ordinary people, groups, and organizations can serve as network gatekeepers, who select which information to share within the network and, in so doing, bridge different network clusters together (Nahon & Hemsley, 2013).

Previous studies have provided empirical evidence suggesting that both individual and organizational actors function as sources and spreaders of climate change attention within Twitter. On one hand, news media act as the major source of climate change attention on this platform (Kirilenko et al., 2015; Kirilenko & Stepchenkova, 2014; Painter et al., 2018). Meanwhile, through tweeting and retweeting, political elites generate spikes of attention about climate change (Stier et al., 2018). And, advocacy organizations strategically use Twitter to engage the public and mobilize public attention about climate change (Hestres, 2014; 2015). News, politics, and advocacy actors all represent influence from institutions. Just as agenda setting and agenda building theories predict, this body of research seems to uphold that organizational actors should act as the major influencers of climate change attention on Twitter.

On the other hand, individual users retweet information from organizational actors and, thus, contribute to spikes of attention on Twitter as the critical periphery in diffusion processes. At least one study found that the aggregated attributes by peripheral users to spread the attention is comparable to that of core actors (Barberá et al., 2015). Furthermore, through interpersonal communication, individual users also influence other individual actors on Twitter. For example, tracking Twitter traffic after the release of the United Nations Intergovernmental Panel on Climate Change (IPCC) report in 2013, Newman (2017) found that most propagated tweets about this report came from individual actors. Taken together, a growing number of studies support the fact that individual actors, independent climate change activists and concerned citizens, play an equally important role in the diffusion of climate change attention on Twitter.

Typically, organizational actors have more Twitter followers (Kwak, et al., 2010; McCorriston et al., 2015) and are more likely to act as sources of climate change attention than individual actors. However, the underlying structure of the retweet network challenges the power of traditional gatekeepers (i.e., organizational actors) in directing the public's attention to the climate change issue, as I explained in Chapter 4. As a reminder, to more effectively observe the dynamics of attention creation and spread among different types of actors, I developed an automated method to typologize Twitter actors at scale. Leveraging this method, I ask:

> RQ1: Which type of actors tend to be the major source of retweets and which tend to be the spreader of the tweets about climate change issue? How do these patterns change over time?

The Intermedia Diffusion of Climate Change Attention

In this section, I expand on research on the intermedia diffusion of attention, particularly related to the issue of climate change. The diffusion of public attention happens more quickly in today's hybrid intermedia environment, in which Twitter plays one part. As Chadwick (2017) pointed out, the key characteristics of the contemporary media system is "hybrid mediality" (p. 64). That means political actors and traditional media outlets like radio, TV, and newspaper have adopted new communication technologies and expanded their influence to digital media; meanwhile, ordinary people influence politicians and news media through social media. Accordingly, a wide array of actors (both organizational and individual) across various media platforms can mediate "political information cycles" (p.6), or specific events in which public attention evolves. The hybrid mediality highlights the way different types of actors compete for attention as a resource to gain preeminence (Chadwick, 2017). While recognizing this growing hybrid mediality, existing studies on intermedia agenda setting and network information diffusion frequently fall short in sorting out or accounting for the complicated relationships between and among different types of actors across various media platforms—a point I brought forward in Chapters 2 and 4.

As an extension of agenda setting theory (McCombs, 2014), intermedia agenda setting theory takes into consideration the transfer of attention between media outlets (Reese & Danielian, 1989), but the key limitation of the theory is that it only focuses on the media level. As I mentioned in Chapter 4, using this theory, many researchers have found that Twitter attention and news attention are interdependent (see e.g., Jones-Jang et al., 2020; Russell Neuman et al., 2014). However, these studies treat Twitter attention as a proxy for public attention and overlook the presence and influence of traditional gatekeepers on Twitter (i.e., news media, politicians, advocacy groups etc.). And yet, it is possible that traditional gatekeepers may be the actors within Twitter responsible for generating news attention beyond this platform. For example, Harder et al. (2017) separated Twitter users into different actor categories and found that only tweets published by political and news actors predicted online news attention about the 2014 Belgium election. Although their study only focuses on a political event, findings may still apply to climate change events because the climate change issue is highly politicized.

Recent studies about online climate change attention have begun to focus on different types of actors on Twitter. These studies have shed light on how climate change attention flows in complicated networks within Twitter (Thorson & Wang, 2019; Wang et al., 2019; Williams et al., 2015). However, these studies still rarely consider comparisons of climate change attention *within* Twitter and *outside of* Twitter. In real-life events, the boundaries between mass media and Twitter are blurry (Lazer, 2020). For example, mass media attention sometimes drives the most popular topics on Twitter (Marchetti & Ceccobelli, 2016). Thus, as an extension to these studies, scholar can consider combining the impact of other media platforms outside Twitter (Pearce et al., 2014).

In Chapter 3, I examined the intertwined relationship between and among Twitter, news, and public attention, but, in that chapter, I treated Twitter as an aggregated attention of different types of users on Twitter. Then, in Chapter 4, I classified Twitter users into five distinct and mutually exclusive actor categories—individual, political, news, advocacy, and other organizational actors. To understand the diffusion of attention across different media platforms more accurately, I ask:

RQ2: How do retweet patterns across actor types within Twitter and public attention outside Twitter respond to each other?

RQ3: How do retweet patterns across actor types within Twitter and online news outside Twitter respond to each other?

Event Variation

For several reasons, it is necessary to compare the diffusion of attention on Twitter with the spread of attention across different media outlets during distinct event contexts. First, real-life events often trigger different patterns of public attention. As illustrated in Chapter 2, some events raise high levels of public attention while others do not. For example, consider social movement events. Twitter mobilized the public and elites to take collective action in contemporary social movements, such as Arab Spring and the Black Lives Matter (e.g., Freelon et al., 2018; González-Bailón et al., 2013; Lotan et al., 2011). However, most online mobilizations fail to raise any attention. For instance, examining petitions posted on U.K. governmental sites, Margetts et al. (2016) found online petitions were largely unsuccessful at reaching large numbers of people. The climate change issue is another case that has raised little grassroots activity in the United States (McAdam, 2017), despite the fact that climate change advocacy groups have adopted communication technologies to strategically mobilize public attention on digital media (Hestres, 2014).

Second, the process of how attention spread differs by event contexts. Therefore, the relationships between public attention and traditional gatekeepers are also likely to be different across event contexts. For example, Nahon et al. (2013) found news media tend to raise public attention on Twitter after unexpected events. Neuman et al. (2014) found that for issues or events related to security, crime, and drugs, public attention follows news media attention, but for other issues such as gun control, natural disasters, and LGBT rights, public attention drives news media attention. Considering the issue of climate change, existing studies have credited different types of actors and media platforms as leading actors in the diffusion of public attention surrounding climate change events. For example, soon after the release of the IPCC report in 2013, the top shared tweets originated more from non-elite Twitter users, such as concerned citizens, climate change supporters, and independent bloggers than from elite users, such as new media outlets and politicians (Newman, 2017). Meanwhile, Pearce et al. (2014) found that climate change advocacy groups initiated campaigns but relied on news coverage to attract wider attention. However, in the case of extreme weather events, individual actors directly tweeted about climate change without mediation from news media (Kirilendo et al., 2015).

Third, analyzing the variation in the patterns and the process of attention diffusion across different events opens up the opportunity to build theory in this understudied area. By observing the heterogeneity found in different events, agenda setting scholars have proposed that news agenda setting effects are contingent on the obtrusiveness of events. In obtrusive events, which the public are familiar with, the salience of public agenda lead to the salience of the media agenda; whereas it is the other way around in the non-obtrusive event, which are foreign and remote to the public (Rogers & Dearing, 1988). However, empirical research does not appear to uphold this theorization. For example, Neuman et al. (2014) found that public attention (using Twitter, online forums, and blogs as a proxy) preceded media attention during the recent wars in Iraq and Afghanistan. As such, public attention is not easily generalizable across different contexts or events.

The heterogeneity in the patterns and diffusion process of attention discovered in different event contexts also connects to what Nahon perceived as the “conditions” to determine when the role-switching moment happens in the network gatekeeping process. Previous empirical studies have paid considerable attention to attempting to identify which types of actors serve as influencers in information diffusion processes (see e.g., Bakshy et al., 2011; Cha et al., 2010). For example, Bakshy et al., (2011) found that it is hard to predict who became influential as the relationship between different types of actors repeatedly shifts and becomes increasingly intertwined and interdependent. Thus, the more important question is not just *who* influences the diffusion of attention, but *when* the contemporary hybrid media system enables which types of actors to influence attention. Nahon (2008) argued that the condition for change exists when the gated have “political power and reciprocal, enduring, and direct exchange with the gatekeepers” (p. 1504). Considering this, I ask:

RQ4: How do different event contexts create opportunities for different sets of actors to be the major source and spreader of climate change attention on Twitter?

RQ5: How do different event contexts create opportunities to change for different sets of actors to influence public attention and online news attention beyond Twitter?

Method

Data Collection

The analyses in this chapter focus on three climate change-related events from 2015. I chose these three events because hourly Google Trends data, which measures public attention, is inaccessible for dates before 2015. As aforementioned, the three events are Earth Day (April 21–23, 2015), the People's Climate Movement protests (October 13–14, 2015), and former U.S. President Barack Obama publishing his first Facebook post about climate change (November 9–10, 2015). As detailed in Chapter 4, Earth Day and People's Climate Movement represent examples of activist campaigns, while Obama on Facebook is an exemplar of a political event.

To measure public attention, I collected Google Trends data by hour for timeframes set for each respective event, using "climate change" and "global warming" as two search queries. For more details about this part of the data collection process, please refer to Chapter 3. Meanwhile, to measure news attention outside Twitter, I collected news coverage data from LexisNexis using the same keywords I used when collecting Google Trends data for these events —"climate change" and "global warming." Using this approach, I collected 493 news stories for the Earth Day event, 358 news stories for the People's Climate Movement event, and 465 news stories for the Obama on Facebook event, meaning in total I gathered 1,316 news stories across all three events. I used the python library Beautiful Soup to extract the publishing time of every news story, so to aggregate the online news data to create an hourly timeseries. To measure the retweeting patterns, I used the retweet data about the three focal events from Chapter 4. The retweet network contains 114,380 retweets for the Earth Day event, 97,492 retweets for People's Movement, and 76,440 for Obama on Facebook.

Since the retweet network only includes the retweets, I traced all the original tweets that were created during the timeframe from the database of Tweets described in Chapter 4. The Earth Day event had 8,675 original tweets, the People's Movement had 8,535 original tweets, and the Obama on Facebook had 7,682 original tweets. I combined the number of retweets and the number of original tweets to calculate the retweeting patterns for each type of user. The measurement of retweeting patterns reflects the extent to which each type of actor spread information related to these climate change events on Twitter. Table 11 summarizes the data description and the timeframe of each event.

Table 11

The Data Description of Each Event

	Earth Day	People's Movement	Obama on Facebook
Timeframe	3 days (April 21–23, 2015)	2 days (October 13–14, 2015)	2 days (November 9–10, 2015)
Total Retweets	114,380	97,492	76,440
Total Original Tweets	8,675	8,535	7,682
Total Online News	493	358	465
Max Search Index	196	148	182

Analysis Approach

To understand the characteristics of each retweet network, I first conducted a basic descriptive network analysis. Specifically, I examined the size, density, reciprocity, and distribution of degrees for each retweet network. Reviewing the retweet network for each of the three climate change events enabled me to gain a better understanding of the global environment or context of each event.

To answer my RQ1, which examines which types of actors constitute sources and spreaders of climate change attention on Twitter, I used R to code each retweet (i.e., the edges in the retweet network) by their direction. For example, if an individual actor retweeted an individual actor's retweet, I coded the retweet as "individual to individual." For each type of actor, I calculated their source ratio for each event, meaning the total number of retweets originating from each type of user and divided it by the total retweets within the entire retweet network pertaining to each event. I calculated the spreader ratio using the total number of retweets that each type of user sent and divided it by the total retweets within the event's retweet network.

To examine how the role of retweet origins and spreaders changed over time, I used an R package networkDynamic and created retweet networks for each event for each hour within a predetermined timeframe. Specifically, the retweet data from Chapter 4 contained 3 days of data for Earth Day (the day before, of, and after the event), 2 days of data for the People's Climate Movement (the day before and the day of the event), and 2 days of data for Obama on Facebook (the day of and after the event). Thus, I created 72 retweet networks for the Earth Day event and 48 retweet networks for both the People's Climate Movement and the Obama on Facebook event. I compared the average indegree centrality of each type of actor across the dynamic networks in each event. The indegree centrality is the number of times a user is retweeted and indicates to what extent a user served as a source in the retweet network.

To answer RQ2 (i.e., how will the retweets by each type of actor on Twitter and public attention correlate over time), I conducted five pairwise Granger causality tests between public attention and the activities of spreading influential climate change tweets of each type of actor on Twitter. To answer RQ3 (i.e., how will the retweets by each type of actor on Twitter and online news attention outside Twitter correlate over time), I conducted five pairwise Granger causality tests between online news attention and the retweet patterns of each type of actor on Twitter. As mentioned earlier, the retweet patterns not only include the volume of retweets, but also the volume of tweets being spread during the timeframe. Unlike what I did in Chapter 3, I did not put all the variables into a VAR model, because they are not endogenous to each other (the assumption of a VAR model) – the Twitter actors are nested underneath Twitter platform. Treating them as endogenous variables with public attention and news attention outside Twitter overlooks the nested relation among them. To answer RQ4 and RQ5, which ask about the even opportunities for Twitter actors to influence news attention and public attention beyond Twitter, I replicate the same analysis to three climate change events.

In the time series analysis, I chose hours as the temporal aggregation for retweets, Google Trends, and news data, because Twitter is a fast platform where about half of all retweets happen within a few short hours following the publication of the original tweet (Harder et al., 2017; Kwak et al., 2010). I selected the number of lags by each pair of Granger Causality test based on the information criteria such as AIC, HQIC, and SBIC. The resulting time series data from Twitter, Google Trends, and online news stories each include 72 data points for the Earth Day event and 48 data points for the People's Climate Movement event and Obama on Facebook event. Lastly, I normalized each time series data into z-score before performing the Granger causality tests.

Results

Basic Network Metrics

The basic network metrics, as shown in Table 12, reveal three main highlights. First, in terms of the size of retweet networks, Earth Day's network was the largest, garnering the most users (77,605 users) and retweets (114,380 retweets), and Obama on Facebook was the smallest, attracting the fewest number users (57,128 users) as well as retweets (76,440 retweets). Second, all three retweet networks have relatively small reciprocity, meaning that users rarely mutually retweeted one another. That said, among events, users involved in the Earth Day event reciprocally retweeted one another more than users engaged in the other two climate change events. Third, in terms of the structure of retweet networks, each network has low density, suggesting Twitter users engaged in the different events were only loosely connected with each other.

Table 12

Retweet Network Metrics of the Three Climate Change Events in 2015

Network	Earth Day	People's Movement	Obama on Facebook
Nodes (users)	77,605	73,178	57,128
Edges (retweets)	114,380	97,492	76,440
Reciprocity	0.01	0.005	0.006
Density	1.90E-05	1.82E-05	2.34E-05
Average degree	2.9	4.2	2.9
Average indegree	1.5	2.8	1.5
Average outdegree	1.5	1.3	1.3
Max indegree	2,749	2,008	2,310
Max outdegree	576	367	390

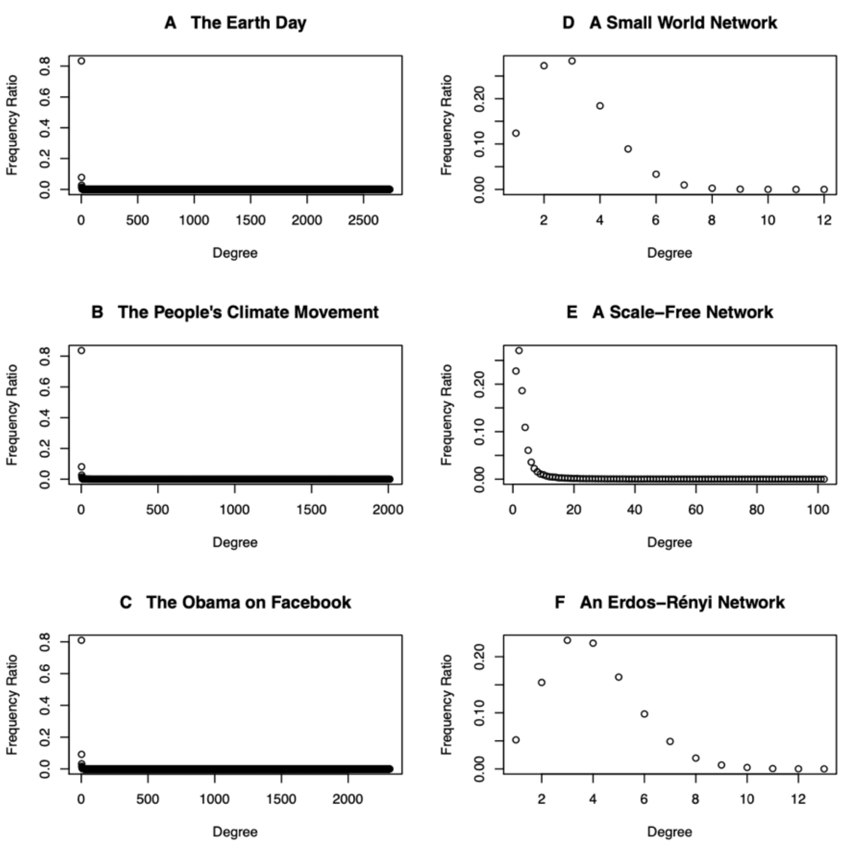
Notes: The retweet network has directions, which indicate the information flow from the original source to the spreader. Nodes, edges, reciprocity, and density all describe the characteristics of the network environment. In a retweet network, the nodes are users and edges are retweets. Reciprocity means the likelihood that users in a directed network will be mutually link. A network density means the ratio between the actual connection and the potential connection in a network could possibly have. Degree, indegree and outdegree all describe the centrality of each user in the retweet network. The degree means the number of times a user being retweeted and retweet. Indegree means the number of times a user is retweeted. The outdegree means the number of times a user retweet.

I also examined the degree distribution across each of three retweet networks (see A, B, and C in Figure 10). Accordingly, the degree distributions, represented in the figure, indicate that more than 80% of users in each of the three retweet networks only have about 1 degree, meaning that they only retweeted once or other users only retweeted them once. To explain how climate change event retweet networks' structures differ from standard types of networks, I simulated three standards types of networks—a small-world network (Figure 10D), a scale-free network

(Figure 10E), and a random network (Figure 10F). In a small world network (Watts-Strogatz network), two nodes (in this case the users) are only 6 degrees away from each other. In a scale-free network (Barabási-Albert network), only a few nodes have significantly high degrees, while the majority have only a few degrees; its degree distribution is a power-law distribution. In a random network model (Erdős-Rényi network), each node is randomly connected, the degree distribution of nodes closes to a normal distribution. The structure of three retweet networks align most closely with the scale-free network. That is, only a few users have significantly high connections (either retweeted or being retweeted) while the majority of other users only have a few connections in the retweet network.

Figure 10

Comparison of the Degree Distributions of Climate Change Event Retweet Networks



Notes: In A, B, and C, each node represents a Twitter user.

Retweet Sources and Spreaders

The first part of RQ1 asked which type of actors served as major sources of retweets and which types of actors served as major spreaders of climate change attention within Twitter. Figure 11 presents these results. In terms of sources, news media outlets were the top source of retweets across all actor categories in all three events. Specifically, 31%, 37%, and 35% of retweets originated from news media outlets on Earth Day, People's Climate Movement, and Obama on Facebook, respectively. Political actors were the least common original source across all events. Specifically, 14%, 9%, and 11% of retweets originated from political actors on Earth Day, People's Climate Movement, Obama on Facebook, and. However, this finding may be a byproduct of the fact that there are far fewer of these particular actors within these three retweet networks.

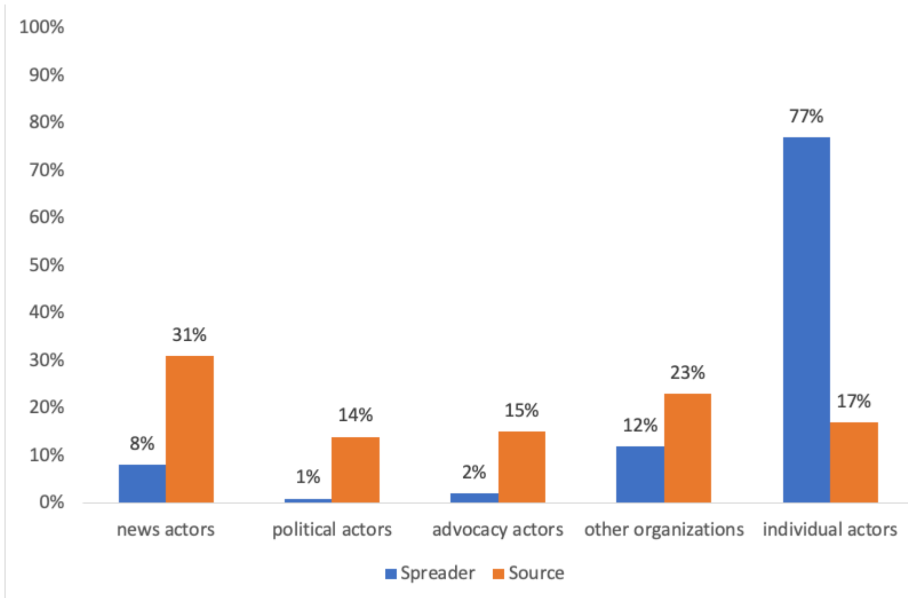
In terms of spreaders, individual actors functioned as the top spreaders of information across all three events. Specifically, individual users accounted for 77%, 79%, and 75% of retweets pertaining to Earth Day, People's Climate Movement, and Obama on Facebook respectively. Political actors and advocacy actors were the least likely to retweet across all events. Political actors accounted for about 1% of retweets and advocacy actors accounted for about 2% in all three events.

Overall, the spreader ratios and the source ratio did not show much variability across the three events. Individual actors were the major spreaders because they consistently retweeted more than being retweeted. Organizational actors served as the major source of retweets related to the three selected climate change events, as they were retweeted more than they retweeted others.

Figure 11

The Sources and Spreaders of Climate Change Attention by Event

A Earth Day



B People's Climate Movement

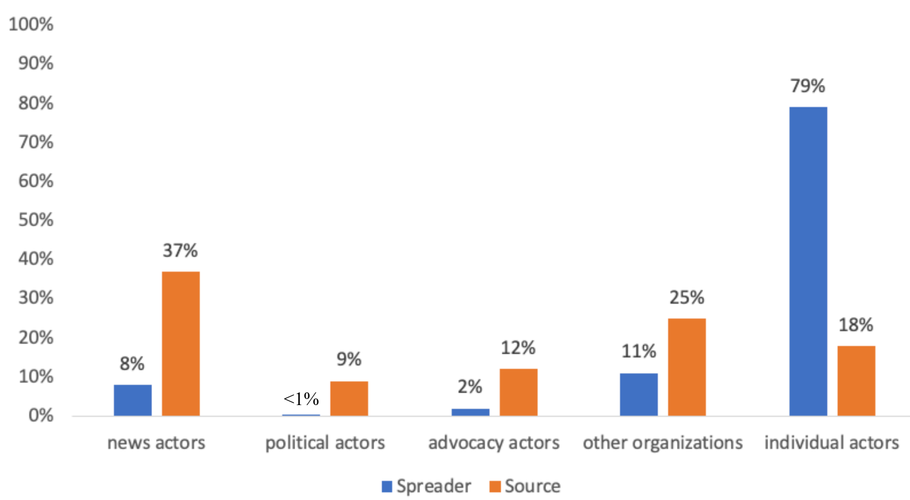


Figure 11 (cont'd)

C Obama on Facebook

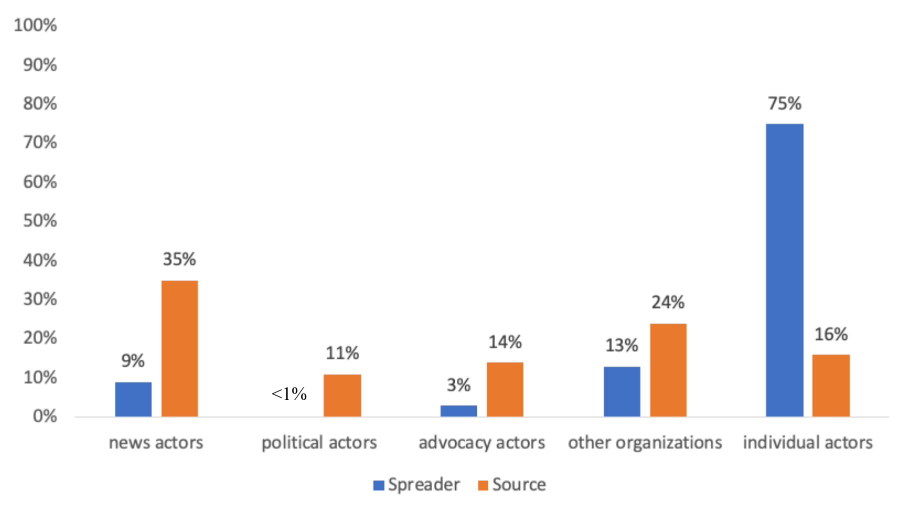


Table 13 shows the source of retweets breakdown by each type of actors. A general overview of the source ratios shows not much variability across all three events. Further investigations of the source ratio for each type of actors reveal three key insights. First, news media is the top source of retweets from individual actors, but it does not monopolize the source of retweets in all three events. On average, around 30% of retweets published by individual actors came originally from news actors. Other organizational actors were the second major source of retweets for individual actors. In fact, across the three events, other organizational actors accounted for nearly a quarter of all retweets shared by individual actors. As a quick reminder from Chapter 4's findings, the other organizations include a wide range of organizational actors, including celebrities, educational institutions, companies, climate change scientists, and professionals affiliated with a wide range of organizations. Thus, news media seems to still hold the power over agenda setting at least surrounding the three events, but individual actors also frequently forwarded tweets from other non-news organizational actors.

Table 13

Source Ratios for Each Type of Actor

	news actors	political actors	advocacy actors	other organizations	individual actors
Source:			Earth Day		
News actors	44%	13%	24%	27%	31%
Political actors	10%	55%	7%	11%	15%
Advocacy actors	11%	8%	34%	15%	14%
Other organizations	20%	19%	21%	32%	22%
Individual actors	15%	5%	14%	15%	18%
Source:			People's Climate Movement		
News actors	49%	21%	26%	31%	36%
Political actors	4%	31%	4%	5%	8%
Advocacy actors	11%	11%	33%	14%	12%
Other organizations	22%	30%	23%	32%	25%
Individual actors	14%	7%	15%	17%	19%
Source:			Obama on Facebook		
News actors	51%	16%	27%	30%	35%
Political actors	8%	43%	7%	8%	11%
Advocacy actors	9%	6%	33%	14%	13%
Other organizations	20%	29%	21%	32%	24%
Individual actors	12%	6%	14%	16%	17%

Notes: The table shows source ratio for each type of user. All values total to 100% by each column in an event. For example, in the Earth Day event, to calculate the source ratio from political actors for the news actors, I used the total number of retweets by news actors that were originally published (tweeted) by political actors divided by the total number of retweets by news actors. The resulting 10% indicated that 10% of the retweets by news actors originated from political actors.

The second insight gleaned from these results is that individual actors are also a source of retweets. Individual actors were the third most common source of retweets for individual actors. Specifically, approximately 18% of retweets by individual actors originated from other individual actors across the three events. These numbers suggest that interpersonal communication among individual users accounts for about a little over one-sixth of the diffusion of climate change attention within Twitter. Although intuitively, organizational users accounted for around 80% of retweets published by individual users, the latter are also sometimes the source of retweets for the former. In the three events, around 14% of retweets by news actors, 14% retweets by advocacy actors, 16% retweets by other organizational actors, and 6% retweets by political actors came from individual actors. Thus, although organizational actors serve as the primary source of information, individual actors also serve as sources of information for organizational actors.

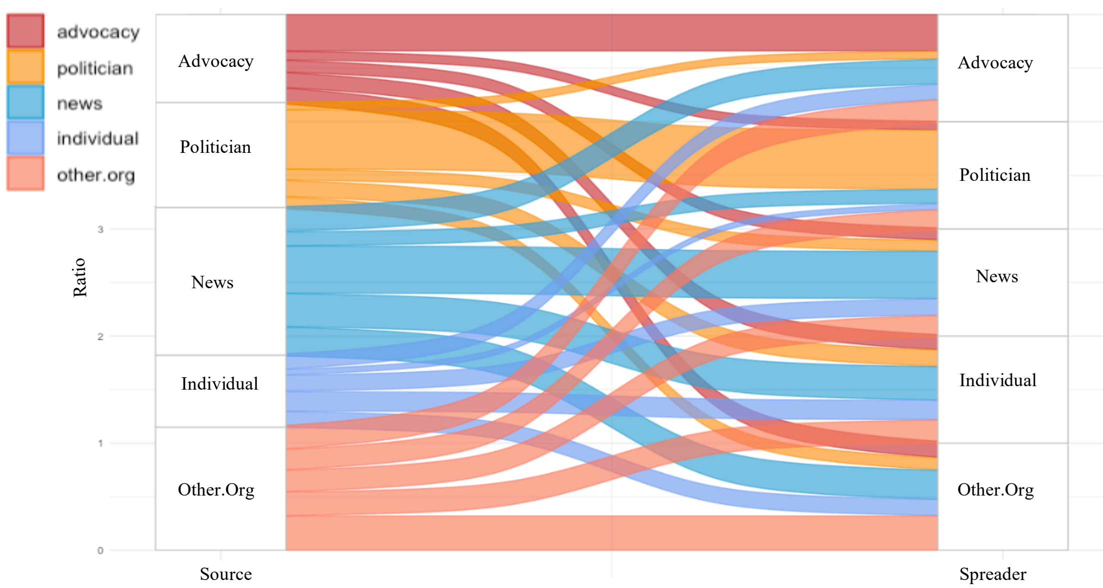
Individual actors retweeted the least from advocacy and political actors. In all events, only an average of 13% retweets by individuals originally came from advocacy groups. About 11% of retweets by individual actors originally came from political actors. This finding about political and advocacy groups runs contrary to previous research, which found that the most retweeted users were the source of a fourth of all retweets (Kirilenko & Stepchenkova, 2014). More specifically, based on a random sample of Tweets from a non-event period, Kirilenko and Stepchenkova found that advocacy groups and news media were instead the most common source of retweets.

The third insight revealed from the data is the strong homophily between organizational actors in all three events. As shown by Figure 12, which visualizes the results presented in Table 13, Tweets by news, political, advocacy, and other organizational actors were most likely to come from their peers. For example, about 48% of retweets by news actors originated from other news actors. Likewise, political actors retweeted mostly content published by other political actors. About 43% retweets by political actors came from other political actors in the three events, although political actors seem to have more variance across events (31-55%) than news actors (44-51%). This strong homophily is perhaps because organizational users on Twitter tend to follow each other.

Figure 12

Visualization of the Source and Spreaders Across Climate Change Events

A Earth Day



B People's Climate Movement

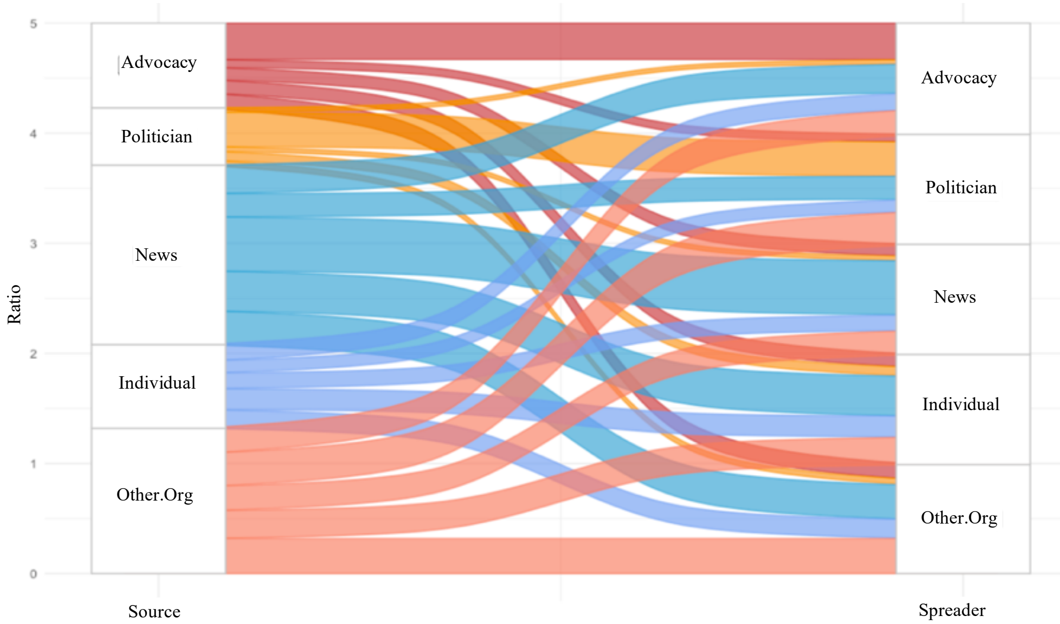
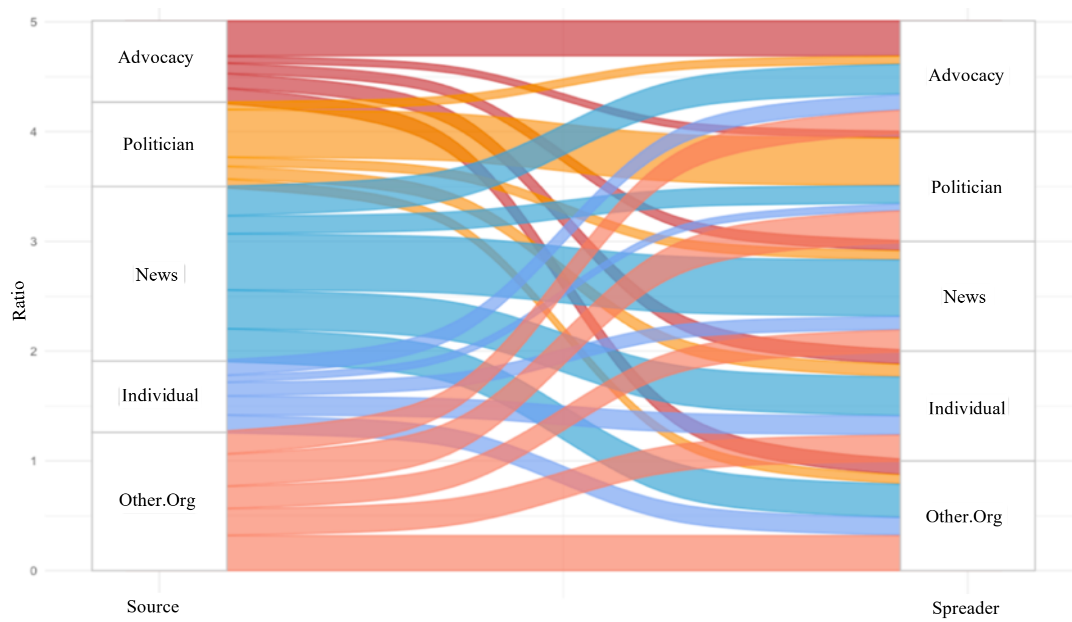


Figure 12 (cont'd)

C Obama on Facebook



Notes: The Sankey diagrams are visualization of Table 13. Each color bar represents a type of Twitter user. The width of the color bar represents how much information is flowing from the source to the spreader.

In summary, these findings suggest that the answer to the first part of RQ1 is that news actors tend to be the top source of climate change information in general, but news actors are not so dominant that they monopolize the diffusion of climate change attention on Twitter. Other non-news organizational actors and individuals all share the role of being a source for the diffusion. Individual actors tend to be the spreaders of information from organizational actors. That said, individual actors also occasionally serve as sources of information for organizational actors. Also, each type of organizational actors was the largest source of information for peers within their same actor category. Lastly, there is little variability across the three events in terms of source ratio and spreader ratio.

Dynamic Changes

In terms of the second part of RQ1 (i.e., how the roles of actors change over time), Figure 13 presents the results. Specifically, Figure 13 shows how the average retweets originated (average indegree centrality) from of each type of actor changes by hour across each of the three events.

A quick comparison of these graphs illustrates that either news actors or political actors are the top source of retweets across all events almost all the time. Accordingly, these two actor types are the most likely to generate spikes of attention, at least pertaining to these climate change events. However, occasionally, individual actors also served as the top source of information. For example, during Earth Day, in the first and the 27th hour observed, individual actors generated more average retweets than other type of actors. Furthermore, during the People's Climate Movement, particularly amid attention spike hours, individual actors acted a larger source of information (retweets) than political actors and advocacy groups. Collectively, these patterns suggest that different types of actors assume the role of source and spreader; that is, these roles are not fixed but change over time.

More importantly, a comparison between the graphs of each event reveals substantial variation in the patterns of attention and the sources of attention during spikes. The People's Climate Movement is the most different event among the three events. In the People's Climate Movement, the pattern of the attention revealed only one huge spike after the event happened. During the spike time, news actors were retweeted the most. Meanwhile, people also retweeted other types of actors more during spikes than they did during non-spike hours, generating repeated synchronization of attention. That is, all types of actors coalesced around retweeting about climate change and, in turn, they together further drove up attention spikes. All types of actors collaboratively created momentum for the movement for about 5 hours. Perhaps, as a result, the strength of attention (shown by the average retweets at peak points) is much higher than the other two events. However, in just 2 hours, spikes dwindled and returned to the typical retweet patterns (see Figure 13B).

Figure 13

The Changing Sources of Attention by Hour in the Three Events

A   Earth Day

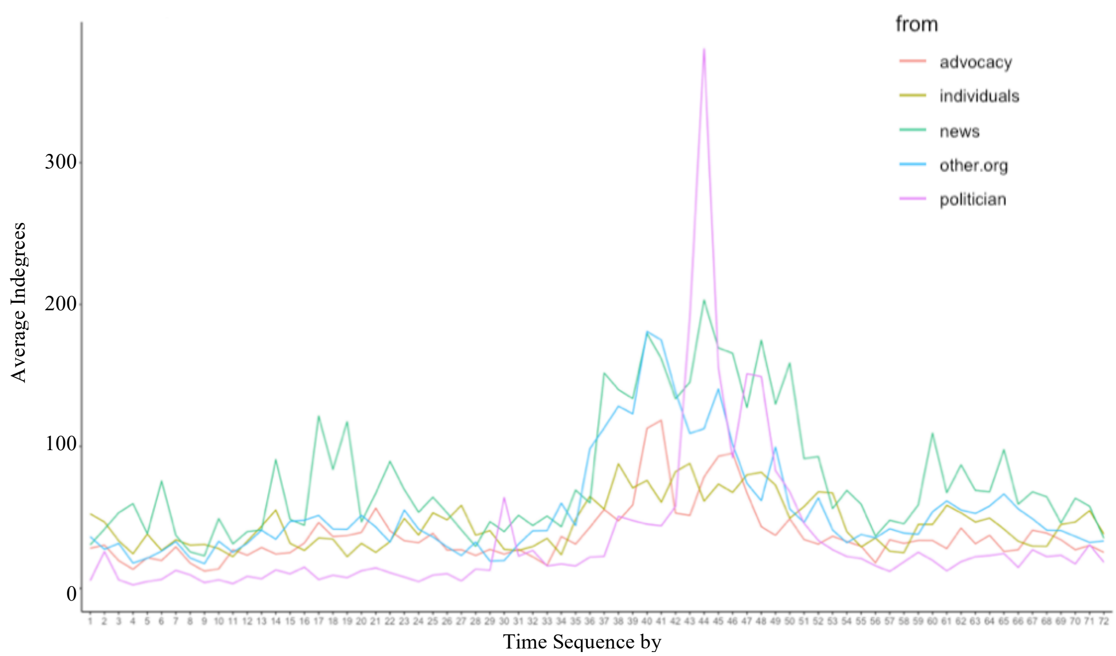
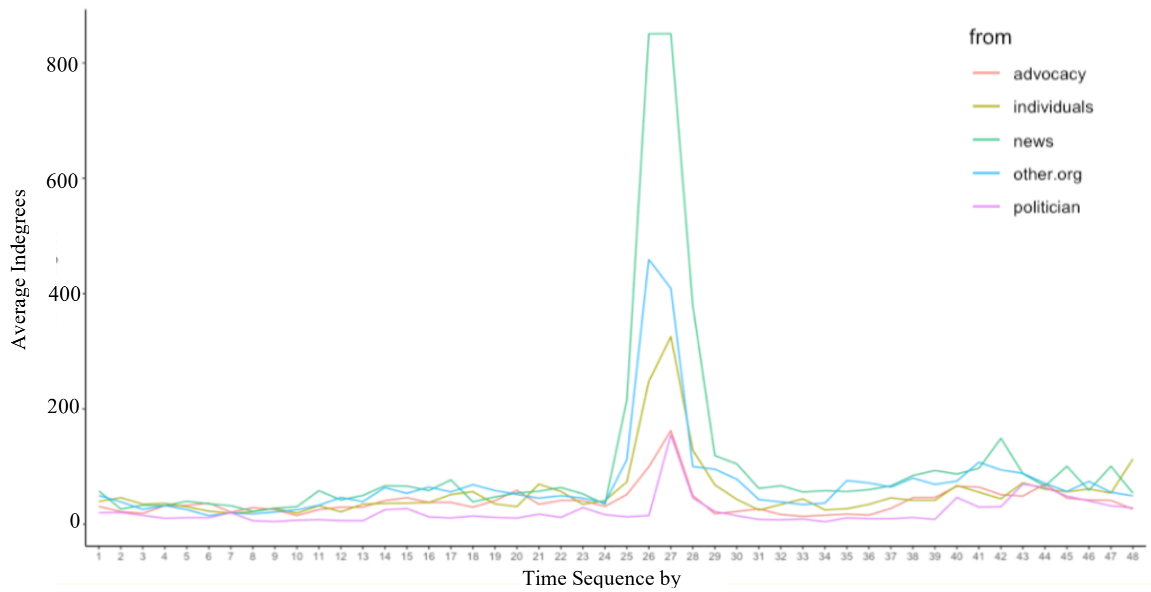
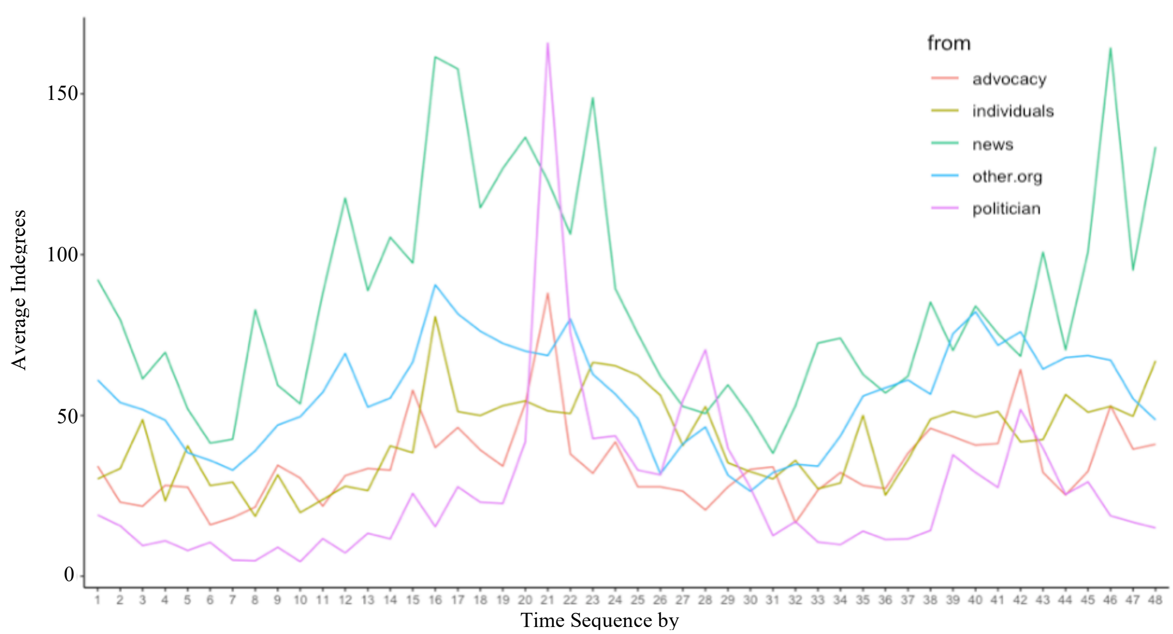


Figure 13 (cont'd)

B People's Climate Movement



C Obama on Facebook



Notes: The three line charts shows the changing sources of climate change attention from each type of actors hour by hour. The x-axis is the mean average indegrees of each type of user, meaning how many times on average the tweets of a type of actors were shared.

In the Earth Day event, political actors were the top source for the largest spike of retweets. Meanwhile, news media were most retweeted in a few clusters of smaller attention spikes before, during, and after Earth Day. Additionally, the graph for this event, in particular, suggests that more enduring attention spikes integrated other actors. For example, after Earth Day, news actors were most retweeted in a cluster of spikes. At the same time, tweets from individual actors and other organizations also corresponded in a cluster of spikes.

During the Obama on Facebook event, news actors remained the top source of tweets most of the time. However, unlike the People's Climate Movement, actors were less integrated. When the White House released the breaking news about Obama opened his Facebook account on November 9, 2015, news and political actors were most retweeted in multiples spikes, but all other actors did not simultaneously integrate with these spikes. Considering this finding and the fact that the Obama on Facebook event had the least number of retweets among the three events, it is possible that less consistent synchronization and integration among actor types leads to less attention on Twitter.

In sum, to answer the second half of my first research question, these findings suggest that although news and political actors continue to be the top sources of attention on Twitter, individual actors occasionally also acted as the top source. Thus, the role of gatekeeper seems to change over the time. Lastly, findings from this section reveals that each event shows a distinct pattern of attention and attention diffusion process on Twitter. Compared to events that sparked less Twitter attention, events with more Twitter attention are associated with repeated synchronization and integration of attention from all types of actors.

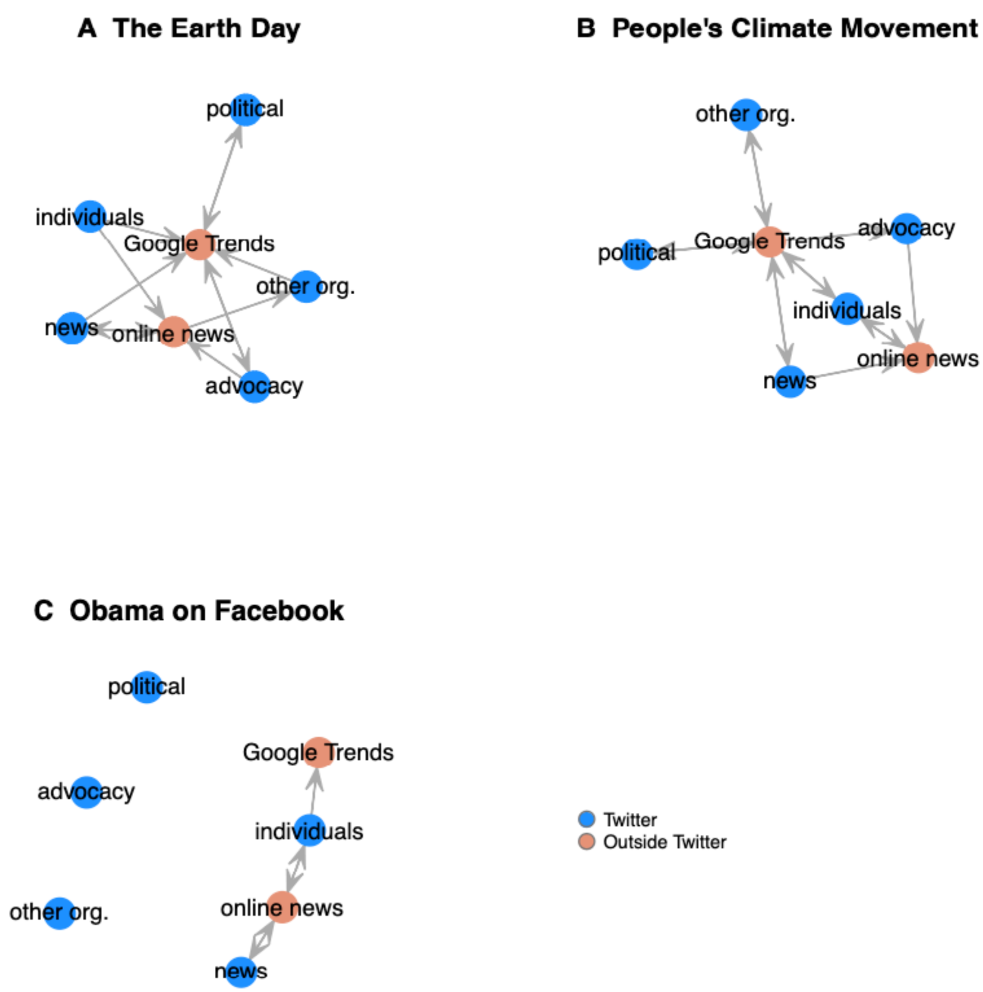
Intermedia Diffusion

My second research question examined the relationships between influential tweets by each type of actor and public attention over time, and my third question considered the relationships between influential tweets by each type of actor and online news attention outside of Twitter over time. Based on the results of the Granger Causality tests, there appears to be different patterns of intermedia diffusion of climate change attention beyond Twitter. However, there also appears to be substantial variance between events in terms of the two-way relationships between influential tweets by each type of actor and attention outside Twitter. I visualized the Granger Causality relationships as a network for each event (see Figure 14).

In every event, individual actors' retweeting activities within Twitter predicted public attention (measured by the normalized Google Trends Index) and online news attention (measured by the normalized number of news articles published by online news websites). This finding is unsurprising; an event becomes newsworthy upon drawing a large volume of attention among Twitter users (Nahon et al., 2013). But these relations between the retweeting activities of individual actors and public attention, and that with online news, were not mutual in all three events. For example, in Obama on Facebook and Earth Day, online news did not predict the retweeting activities of individual actors on Twitter. This suggests that although previous studies found that most tweets about climate change cited URLs linking to a professional news websites (Kirilenko et al., 2015; Veltri & Atanasova, 2017), online news in these events did not directly predict the retweeting activities of individual actors.

Figure 14

Visualization of Granger Causality Relations Test Results



Notes: Each blue node represents actors from Twitter. The red nodes represent online news and Google Trends data. A link between two nodes indicates that one Granger Causes the other. The direction of the edge indicates which node precedes the other. See Appendix E for the numeric results of these Granger Causality tests.

As for the organizational actors within Twitter, the results show more variation between events, which I sum up through four main points. First, public attention did not always respond to organizational actors within Twitter. For example, the volume of tweets by news actors predicted public attention for Earth Day and the People's Climate Movement, and the volume of tweets by political, advocacy, and other organizational actors predicted public attention for Earth Day. The retweeting patterns from political and other organizational actors predicted public attention for the People's Climate Movement, but in the Obama on Facebook event, no organizational actors predicted public attention; only individual actors predicted public attention, as mentioned earlier.

Second, the retweeting patterns of organizational actors within Twitter mostly *responded* to public attention outside Twitter. For example, in the People's Climate Movement event, public attention predicted the Twitter behavior of political, advocacy, and other organizational actors within Twitter. It is possible that some organizational actors used Google Trends to monitor the trends in public attention to strategize their Twitter content and usage. In contrast, for the Obama on Facebook event, public attention predicted none of the Twitter behavior of any organizational actor.

Third, online news attention outside Twitter responded to the retweeting patterns of organizational actors on Twitter. News actors predicted online news attention outside of Twitter for all three events. Advocacy and other organizational actors within Twitter predicted online news attention for Earth Day, but only political actors within Twitter predicted online news attention for the People's Climate Movement. For the Obama on Facebook event, non-news organizational actors did not predict online news attention beyond Twitter.

Lastly, organizational actors within Twitter responded to online news attention. For example, online news predicted the retweeting patterns of news and other organizational actors within Twitter for Earth Day. Online news also predicted news actors within Twitter for the Obama on Facebook event. I will come back to discuss this more later. However, online news predicted none of the organizational actors' Twitter behavior for Peoples' Climate Movement.

Taken collectively, the analysis indicates that organizational actors involved in the Obama on Facebook event were the least correlated with public attention and online news attention outside Twitter. I interpret this limited connection in different ways. Some may attribute it to the fact the event also had the least amount of attention within Twitter as well. Another explanation could be that government-initiated events, such as Obama on Facebook, are automatically newsworthy, whereas activist events such as People's Climate Movement and the Earth Day need to prove their newsworthiness by generating public attention. Furthermore, considering that all actors were the least synchronized and integrated for the Obama on Facebook event, another possible explanation is that the event itself is not specifically about climate change. Vraga et al., (2015) have found that on social media, issue-specific communications tend to create greater influence than non-issue specific communications.

In the two social campaign events, advocacy groups predicted online news. This relation mirrors the findings from previous studies about online mobilization; advocacy groups rely on news media outlets to garner attention for events (Freelon et al., 2018). But the Earth Day and the People's Climate Movement events each have different relationships among each type of actor. For Earth Day, each set of actors within Twitter more closely correlated with public and news attention than the People's Climate Movement; this could be because Earth Day is a global campaign while the other is local in the U.S.

In sum, these findings suggest that the answer to RQ2 and RQ3 is that both individual and organizational actors within Twitter connect with public and online news attention outside Twitter over time. Shared among all three events was that tweets from individual actors predicted public attention, and tweets from news actors predicted online news attention outside Twitter. But the interrelation between organizational actors and public attention and news attention varied substantially between events. In other words, while all types of actors appear to connect with attention (i.e., public attention and online news attention) beyond Twitter, which types of organizational actors can influence the attention outside Twitter depends on the event context. Events with high Twitter attention are associated with a spillover effect to the intermedia transmission of attention from the organizational attention on Twitter. This finding suggests a potential relationship, which could possibly answer RQ4 and RQ5. High Twitter attention events create an opportunity for organizational actors on Twitter to influence public attention and news attention outside of Twitter.

Discussion, Implications, and Limitations

In this chapter, I focused on three climate change events and compared the changing roles of different types of actors in the diffusion of climate change attention within Twitter, and moreover, different actors' interactive relationships with public attention and online news attention outside Twitter. The findings show that on the one hand, organizations (news, political, advocacy, and other organizational actors) maintain much of the agenda setting and agenda building power. These types of actors remain the major source of attention on Twitter, at least during the selected climate change events. On the other hand, individual users within Twitter acted as the major spreaders of attention from organizations.

At the same, these findings provide evidence of some limitations of existing agenda building and setting theories in explaining changes in public attention in today's ever-changing hybrid media environment. First, agenda setting and building theories emphasize that organizational actors play a dominant role in shaping public attention and in influencing the diffusion of attention. However, my analysis indicates that individual actors also contribute to these processes, at times, acting as a source of information for traditional gatekeepers. Although generally a relatively minimal source for organizational actors, for Earth Day, individual users were the leading source of attention within Twitter. Arguably, such individual attention can, in turn, influence online news attention and public attention outside Twitter. Individual actors also influenced the diffusion of climate change attention by engaging in interpersonal communication with other individuals within Twitter. Indeed, individual attention to the climate change issue largely follows close ties (Kahan et al., 2012). What my analyses bear out is that Twitter operates with multiple sources of influence, including those born from intrapersonal, interpersonal, and mass forms of communication (Tandoc & Eng, 2017). As Pearce et al. (2019) pointed out, diverse sources influence Twitter; thus, the distribution and diversity of influencers of attention to the climate change issue is complex.

Second, the findings related to my first research question about the sources and the spreaders of climate change-related tweets affirm the findings of other research about the viral diffusion of information online (see e.g., Barberá et al., 2015; Goel et al., 2012; González-Bailón et al., 2013). Similar to these other studies, my findings showed that to sustain attention within Twitter requires the integrated effort of all types of actors to produce moments of repeated synchronization, which then attract even more attention. This finding, for example, echoes González-Bailón et al.'s (2013) research. Examining the online mobilizations associated with the Indignados Movement in Spain, they found that a single group rarely played a decisive role in expanding the global reach of this movement; rather, the "reinforcing interactions" and the "constant information transfer" between opinion leaders and grassroots users within Twitter (p. 959) fed the growth of this movement. In a similar vein, Barberá et al. (2015) showed that both core and peripheral Twitter users collaboratively fueled attention to mass protests within Twitter. In other words, contrary to the traditional theorization about how agenda setting and building unfolds, my research, along with that of other scholars, suggests that both organizational and individual actors together contribute.

Third, agenda setting, agenda building, and intermedia agenda setting theories are not generalizable to explain the transmission of public attention in every event. The findings provide strong evidence of variation in political events and social activism events in terms of the patterns and processes in the diffusion of climate change attention. Agenda setting scholars have noticed event contexts and categorize events by their obtrusiveness, meaning the familiarity of the event to the public. They argued that news media are more responsive than the public for non-obtrusive issues. However, results from this study show that for the three events that are all related to a non-obtrusive issue like climate change, the patterns of news attention in each event is different. Future studies can investigate more ways to categorize the events.

Implications and Limitations

One of the highlights of the findings is the moments when attention from all types of actors repeatedly integrated and synchronized, creating clusters of attention spikes within Twitter, such as in the Earth Day event. Such moments did not surface in the other two events, both of which attracted less Twitter attention and connected less with attention from other media platforms. Taken together, results from the chapter imply a potential association between the high Twitter attention events and the repeated synchronization and integration of attention from all types of actors on Twitter. The high Twitter attention events are also associated with a spillover effect from organizational actors to the attention outside Twitter. Two theories may be relevant to explain why the events with the moments of integration and synchronization generate more attention than those without: Granovetter's (1978) threshold model and the notion of discursive opportunities (Koopmans & Olzak, 2004). Scholars have already used the two theories to explain the diffusion of social movements. In terms of the former, Granovetter emphasized the interdependent and collaborative relation between individual actors in the contagion process. Therefore, when a social issue synchronizes enough attention from different actors within Twitter over the time, then, the attention to said issue or event tends to endure. A recent study by Piedrahita et al. (2018) connected the idea of synchronization to the threshold model and used the idea of synchronized coordination—a classic model to study dynamics in biology and physics —to examine the contagion dynamics of social mobilization. They found that repeated activation of Twitter users increases the likelihood of large-scale contagion online.

Meanwhile, Koopmans and Olzak (2004) argued that three elements—visibility (the exposure of the message), resonance (actors from the public sphere react to the message), and legitimacy (more support than rejection from the public sphere) increase discursive opportunities—chances for information to diffuse across the public sphere. Although given the design of this study it is unclear, it is possible that these moments of integration and synchronization provide discursive opportunities for the diffusion of climate change attention by increasing the visibility and resonance of this information. In short, these concepts of synchronization and integration may represent a theoretically rich opportunity, which could help explain the complexities in the generation, evolution, and diffusion of public attention in the contemporary hybrid media system.

This research also supports the need to consider time as an important factor in the diffusion of attention across media. Specifically, the analysis used dynamic networks to see the changing roles and capacities of each set of actors in the diffusion processes. An analysis of static networks only captures a small snapshot of the diffusion process; they obscure or miss differences across events, which unfold over time. For instance, the dynamic networks in my analysis demonstrate that role-switching occurs within the diffusion process, in that over time, different types of actors assume the roles of gatekeeper and gated. In brief, future communication research should shift more attention from analyzing a static network to analyzing dynamic networks.

As with all studies, this one does not come without limitations. First, this study only conducted a preliminary examination to the structure of retweet networks but did not conduct further analysis to the communities within each retweet network. The basic network metrics showed that Twitter users are loosely connected with each other across all three events. This finding suggests that climate change attention may be spreading only within many small subgroups or communities. As shown by Williams et al. (2015), like-minded users tend to retweet each other and form echo chambers, whereas occasionally, cross-communication between climate change doubters and climate change believers happened, too. Future studies can conduct more advanced network analysis such as community detection to analyze the dynamics of the communities.

Second, this study focused on original sources and spreaders of climate change information across three event-related retweet networks. Although the retweet networks showed flows of attention from sources to spreaders, they did not reflect intermediaries between these two entities, due to limitations of Twitter's API. For example, a user may send a tweet from A → B → C, but the retweet network would only show the path from A → C. To understand the role of intermediaries in the diffusion of attention, future studies can use diffusion trees (Meng et al., 2018), which allow researchers to account for intermediaries in this process.

Moreover, this study focused on the volume of retweets and news coverage, meaning I did not conduct a content analysis of tweets. As mentioned earlier, the structure of retweet networks was loose, and so, it is possible that public discourse varied across different communities, because each individual user may distinctly respond to climate change related (Russell Neuman et al., 2014). Moreover, past research has found that the organizational actors within Twitter each framed climate change differently as well (Stier et al., 2018). Findings from the time series analysis tells us whether an actor from Twitter generally responded to public attention and/or news attention outside Twitter. They are limited to conclude whether the attention from different types of actors support or distort the meaning of the discourse about the climate issue.

This suggests that to understand how to sustain Twitter attention concerning climate change and further sustain its impact on other forms of attention, scholars need to conduct more research in which they focus on climate change communication on Twitter and disaggregate this communication by Twitter users. From a practical standpoint, t is important to learn more about the people spreading awareness and attention as a route to enhance grassroots issue activism campaigns. As Pearce et al. (2014) suggested, influencers on Twitter include not only elites but others, and it is important for researchers to uncover more about the users tweeting about climate change and bringing attention to this major environmental issue.

Lastly, the study only focuses on three events due to the limitation of the historic Twitter data. The future scholars can systematically investigate more events and extend the current approaches to categorize events. As mentioned before, agenda setting scholars have typologied events by the obtrusiveness of the issue that an event is surround by. Other studies classify events by their triggers (Thorson & Wang, 2019) and the levels of media attention received (Anderegg & Goldsmith, 2014). Based the findings about the attention patterns in this chapter, future studies can also categorize events by the patterns of public attention.

Despite these limitations, the study extends the literature by examining the dynamic roles of individual, news, political, advocacy, and other organizational actors in three contextually different climate change-related events. Furthermore, the study also expands the scholarly focus on the diffusion of attention within Twitter to media platforms outside Twitter. The findings showed that news and political actors were the major source of climate change information and that ordinary individual users were the major spreader of the information within Twitter. However, complicating the general understanding among communication scholars, which actors fulfill these two roles is not static, but switches over time. Additionally, in terms of the intermedia diffusion of climate change attention, the accumulated attention from individual actors predicted public attention and online news attention. Twitter, public attention, and news attention are typically intertwined and contingent upon each other, but this is not always the case. A comparison of all three events indicates that attention diffusion patterns and processes vary across event contexts. Lastly, the findings revealed that moments of synchronization and integration across different actors led to sustained attention within Twitter as well as more connection with attention from other media outlets outside Twitter. Taken together, this study challenges some of the underlying assumptions within existing agenda setting, agenda building, and intermedia agenda setting theories. Ultimately, this study sets the foundation for more theory-building to explain the dynamics of public attention, particularly its generation, evolution. and diffusion in the contemporary hybrid media system.

CHAPTER 6: DISCUSSION AND CONCLUSION

This dissertation asked, what shapes the dynamics of public attention to a social issue across media over time? To answer this question, I have used a computational social science approach and examined the evolution of public attention and its temporal relationships with other sources of attention (e.g., news, political, strategic organizational, and individual actors) across media platforms. Setting climate change as the analysis context, I conducted three empirical studies that examined three research goals: (1) to clarify what public attention is and identify a robust way to measure it, (2) to disaggregate attention from different types of actors on social media, and (3) to examine patterns of public attention across different climate-related events.

But what shapes public attention across media over time? A simple answer to the guiding empirical question is that both individual and organizational actors shape public attention, but who takes the lead depends on temporal conditions. I will further illustrate these temporal conditions later in this chapter. At a first glance, this finding seems like common sense. But as Duncan Watts says, social science relies on common sense by testing it and understanding how much it varies by time and culture. Based on sorting out the fragment and paradox in common sense, social scientists build theories, which is systematic knowledge (Watts, 2014). Likewise, what the simple answer means to the theory building about public attention is that prior studies using only agenda setting, agenda building, or gatekeeping theories to explain public attention in the contemporary media system have just seen the tip of the iceberg of its complexities. The media environment nowadays is saturated with individual choices (Edy & Meirick, 2018) and a mix of interpersonal communications and mass communications (Welles & González-Bailón, 2020). As Chadwick argues about the hybrid media system, old media and new media are working together in an integrated mode (Chadwick, 2017). Thereby, this simple answer means that there is not a single theory or a simple dichotomous model that explains the evolution of public attention, rather, the development of public attention goes through pluralistic and dynamic mechanisms (Neuman, 2016). The findings from this dissertation contribute to our understanding of these mechanisms in three ways, as I will explain below.

What is Public Attention and How to Measure It

For the first contribution, findings from this dissertation demonstrate that public attention is conceptually and empirically different from news attention, Twitter attention, and public opinion. To theorize public attention, it is necessary to treat it as an independent analytic category. In this dissertation, I conceptualized public attention as a valuable source in the contemporary media system. I used an alternative approach --people's search behavior on Google to measure public attention. After a longitudinal analysis of public attention, public opinion, news attention, and Twitter attention patterns over 6 years (2011–2016), I found that each of them is distinctive in intensity, volatility, and responses to real-life events. Public attention is less stable than public opinion, affirming what some scholars have predicted (Newig, 2004; Ripberger, 2011). Public attention is less volatile, intensive, and responsive to the real-life events, compared to Twitter and news attention. Thus, previous studies that use Twitter attention or news attention as a proxy for public attention could have overestimated the instability of public attention. My findings also show that daily and monthly news attention, Twitter attention, and public attention correspond with each other over time. Thus, treating public attention as news attention, Twitter attention, or public opinion also overlooks the possible causal relationships among them. However, measuring public attention using Google Trends Index is not a perfect way to reflect the definition of public attention as the attention from the ordinary people. Although Google Trends capture the dynamics of public attention over time, the anonymity of the data creates challenges to clarify the exact level of search behavior from the ordinary people. It is challenging to differentiate whether a search behavior is from an organization or an ordinary individual. It is also challenging to tell the volume of unique individuals who conduct the search and adjust the repeat search behavior from an individual user. The limitation of search data opens opportunity for the future studies to combine survey and people's search behavior to better measure public attention.

Temporal Conditions of Public Attention

The second contribution of this dissertation is about the temporal conditions in the evolution of public attention. In this section, I illustrate the simple answer that I mentioned in the beginning of this chapter with more details. Specifically, I focus on ways to understand the temporal conditions in theorizing the evolution of public attention, based on findings from the empirical analyses. Moreover, I integrate methodological approaches to analyze time series digital trace data to help move forward the theories of public attention.

First, what shapes public attention varies depending on the time scale at which we observe the phenomena. Public attention is entangled with attention from news, Twitter, and strategic organizations across mass media and digital media over time, as the hybrid media system gives the capacity to individual and organizational actors to influence each other. But underlying the interdependence among different forms of attention, we can see that mass media and digital media play distinct roles in shaping public attention. As shown by the results from Chapter 3, Twitter is a fast platform creating strong but transient changes in public attention at the daily level, whereas news is a slow platform influencing public attention at the monthly level. Twitter attention is the most volatile and intensive comparing to news attention, public attention, and public opinion. It takes less than two days for Twitter to influence public attention and news attention. In contrast, it takes about one month for news to influence public attention. The impact from strategic organizational attention (measured via press releases) exists at the daily level but is not sustained at the monthly level. These findings suggest that scholars can extend media effects theories like agenda setting and agenda building by examining the short-term instant effects and long-term accumulated effects of media platforms.

These findings demonstrate the value of conducting times series analysis based on multiple levels of temporal disaggregation as a different lens to examine public attention. The previous studies about public attention often do not consider the difference between short-term effects and long-term, cumulative effects. Methodologically, they tend to choose only one "best" temporal aggregation (either daily, quarterly, or monthly) in time series models that is driven by agenda setting and agenda building theory. But comparing the results from the time series models based on different temporal aggregation can help extend current theories about public attention by examining how causal relationships play out in the in short term versus the long term.

Second, what shapes public attention depends on the dynamic process of attention diffusion across media. The evolution of public attention is a network gatekeeping process. Abbott (2001) pointed out that, in social science, processes have largely disappeared from empirical studies, yet understanding temporal processes are central for theory building (Abbott, 2001). Most previous studies about attention diffusion on Twitter have assumed that organizations and the ordinary people are connected in a stable network structure. My findings from Chapter 5 show that both individual and organizational actors share the role of being the top source for climate change diffusion over time on Twitter. A static look at the attention diffusion network on Twitter suggests that organizational actors are the major source and individual actors are a major spreaders of climate change attentions. In comparison, a dynamic look of the network reveals that sometimes individual actors can become top sources as well. Accumulated attention from individual actors also predicts news attention and public attention beyond Twitter. Echoing Nahon's network gatekeeping theory (2008), these findings show that the role of gatekeeper and the role of the gated in an attention diffusion process can switch among different types of actors over time.

Findings about the network gatekeeping process have also demonstrated the value of examining dynamic processes to more effectively theorize the evolution of public attention as a network gatekeeping process. These findings also suggest the value of conducting dynamic network analysis to examine the attention diffusion process on Twitter. Different from many previous studies that focus on Twitter and only analyze a static network, the strength of dynamic networks is that they reveal the changing importance of each type of actor.

An extension of studying the dynamic process for future studies is to focus on the role of sequence as another temporal lens to examine the network gatekeeping across media. By sequence, I mean the order of users who influence the diffusion of attention. A recent study has shown the importance of analyzing sequences as an approach to understand time as a dynamic process (Peng & Zhu, 2020). Previous studies focusing on information diffusion on Twitter have traced the sequences of spreaders who propagate messages in the diffusion process. They estimated a cascade network, which traces the full path of attention diffusion from source, through intermediaries, and to final receivers (e.g., Goel, Anderson, Hofman, & Watts, 2015; Gonzalez-Bailon, Kaltenbrunner, & Banchs, 2010; Meng et al., 2018). Future research can build on these studies by integrating attention that is outside Twitter to the cascade network.

Third, what shapes public attention varies by event contexts. In this case, time, represented by historic events, becomes a discrete variable (Abbott, 2001). By replicating the dynamic network analysis and time series analysis across three climate change-related events: Earth Day in 2015, The People's Climate Movement in 2015, and Obama on Facebook in 2015, I found that each event shows a distinctive pattern of public attention and attention diffusion process. Specifically, the organizational actors involved in the Obama on Facebook event were the least correlated with public attention and online news attention outside Twitter. In comparison, the communicative behaviors of organizational actors involved in the Earth Day event and those in the People's Climate Movement event were the most connected with those attention outside Twitter. Interpreting this limited connection in different ways, I infer that high volume Twitter attention events are perhaps associated with a spillover effect from organizational actors to public and news attention outside Twitter. High volume Twitter attention events may also be associated with consistent synchronization and integration of all types of actors on Twitter. Or it may because of the initiator of the events, as political elites automatically gain high attention for the event, whereas the other two social movement events need to prove their attention-worthiness. Taken all together, beyond simply observing the heterogeneity of the events, my findings suggest a potential hypothesis to theorize event contexts for the future studies: Compared to events that sparked less Twitter attention, events with more Twitter attention are associated with repeated synchronization and integration of attention from all types of actors. Moreover, events with more Twitter attention are also associated with a spillover effect to the intermedia transmission of attention from the organizational attention on Twitter. These findings extend network gatekeeping theory by suggesting what kind of event contexts may allow certain types of individual actors to become gatekeepers. It also opens a theoretical opportunity to examine the role of repeated synchronization and integration in sustaining public attention. As for the climate change communication professionals, this finding may shed light on how to raise more climate change attention when needed.

In terms of method, these findings about event contexts also show an approach to categorize events based on the attention patterns. Previous studies have shown several possible ways to categorize events based on event characteristics. For example, they categorize events by their obtrusiveness and proximity (Vonbun, Königslöw, & Schoenbach, 2016), by the triggers of events (Thorson & Wang, 2019), or by the level of media attention an event received (Anderegg & Goldsmith, 2014). Few studies classify events by patterns of public attention. For example, Lehmann et al., (2012) classified Twitter attention about different events (measured by hashtags) into four categories: attention concentrated before and during the peak, during and after the peak, symmetrically around the peak, and totally concentrated on the peak. Groß (2019) categorized events into low baseline public attention and high baseline public attention events. He found that in the events with low initial public attention, news attention tends to lead public attention compared to those with high initial public attention. Findings about low attention/high attention events in this dissertation, along with those prior studies show that it may be an effective way to typologize events by their patterns of public attention, creating a pathway to further theorize the event contexts.

Disaggregating Twitter Users

The third contribution of this dissertation is the demonstration of the value of disaggregating Twitter users to understand the dynamic process through which public attention evolves. The majority of existing intermedia agenda setting studies use aggregated Twitter attention as a proxy for public attention, while overlooking the presence and influence of traditional gatekeepers on Twitter. Therefore, their findings are limited to understanding attention diffusion at the media outlet level. In this dissertation, I used an automated classification method to disaggregate Twitter users into five categories of actors (individual, news, political, advocacy, and other organizational actors), I found that Twitter involves a variety of organizational actors and individual actors in the spread of climate change attention—at that patterns of attention diffusion look quite different when this fact is taking into account empirically. Each type of actors on Twitter demonstrate distinctive capacities to drive the spread of climate change attention within and beyond Twitter. For example, I found that individual actors were the major amplifier of organizational attention within Twitter, and their spreading behavior is able to trigger news attention beyond Twitter. Organizational actors often spread the attention from their peers within Twitter, demonstrating homophily, and then influence news attention and public attention beyond Twitter. Thus, Twitter creates more variety of paths to diffuse of climate change attention than intermedia agenda setting has predicted (Bennett et al., 2018). These findings suggest that future intermedia agenda setting studies need to disaggregate Twitter users and give credit to the micro dynamics among the organizational actors, particularly the traditional gatekeepers (news, politicians, and large organizations) and the individual actors in amplifying the transfer of attention across media.

To disaggregate Twitter users, this dissertation provides insights to design an automated classification approach, using machine learning, crowdsourced coding, and a dictionary that I created. I also suggest strategies for labelling data with a quality control system to maintain a good performance of MTurkers, the steps of building a supervised machine learning model and an automatic user classification dictionary. The automated classification method can benefit future intermedia agenda setting studies, especially those that focus on the climate change context.

Limitations and Opportunities for Future Research

First, in this dissertation, I have focused on longitudinal analysis of the six-year climate change attention and then zooms in to three climate change events. The sampling of the events is based on a post hoc selection. That means those events were selected because of their success of driving spikes of attention on Twitter. Future studies should also investigate unsuccessful events—that is, events that did not generate spikes in attention. Specifically, future studies can build on theorizing the event contexts by using the typology that I mentioned earlier to classify events based on the patterns of attention.

Second, this dissertation examined the sources and spreaders of climate change attention on Twitter, assuming the attention is somehow related to the event. It does not further examine the variance of the frames or public discourse across the types of actors. It is quite possible that the frames and discourses appear to have diverse opinions and perspectives of the climate change issue. Analysis at the content level will also be necessary because, as shown by the retweet network metrics in Chapter Five, Twitter users who tweet about climate change are loosely connected with each other. That means there are many subgroups within the retweet network. Perhaps future studies can conduct qualitative analysis to the public discourse or framing analysis to examine how different frames and discourses diverge at the non-spike hours and converge at the attention spike hours. This will help us understand what factors lead to or sustain the moments of synchronization and integration that unites all types of users.

The third limitation is that this dissertation detected the existence of news bots that promote climate change facts on Twitter, but due to the limitation of the historic data and the scope of the dissertation, I did not further systematically examine the bot attention and its interactive relation with other types of actors. More questions about news bots deserve future studies. For example, are there social bots that spread climate change hoax information? What are roles of bots in the climate change attention diffusion process on Twitter? How will it extend the theories about public attention, which are based on mass communication and interpersonal communication? It will be meaningful to have more futures studies to answer these questions.

Conclusion

In conclusion, the dissertation contributes to our understanding of the conceptualization of public attention and who shapes the dynamics of public attention across media over time. Results of the dissertation reveal that public attention is a distinctive category of attention; it is different from news attention, Twitter attention and public opinion in terms of volatility and intensity. The results also reveal that the process through which public attention evolves in the contemporary media system is pluralistic. The agenda setting, agenda building, and gatekeeping theories only partially explain these processes, as both the organizational actors and individual actors influence the evolution of public attention across media. The results show a strong event heterogeneity in terms of the attention patterns and the attention diffusion process, which is a theoretical opportunity for future research on public attention. The results suggest hypotheses that the consistent integration and synchronization of all types of actors on Twitter may produce more Twitter attention and expand the influence of organizational actors to public attention and news attention beyond Twitter. This dissertation also makes methodological contributions to the literature by building an automated classification approach to detect political, news, advocacy, and other organizational actors on Twitter. This dissertation uses longitudinal digital trace data to measure different forms of attention, the choice of temporal aggregation used times series analysis, and analysis of the dynamic networks – all of them have shown the strength of the computational social science analytic approach in studying the dynamics, intertwining, and ever-changing relationships between public attention and other forms of attention. Future studies can advance this body of literature by systematically examining more events based on their attention patterns, the public discourse, and the diffusion of different climate change frames.

APPENDICES

APPENDIX A. Explanation of measurement of sustainability (Chapter 3)

I used Augmented Dickey-Fuller (ADF) test to examine the sustainability of each time series data. Here is the logic: This test is most often used to diagnose whether a time series data is stationary. If a time series is stationary, that means the its historic values can predict the future values, with a mean, variance, and autocovariance remained the same (Box-Steffensmeier et al., 2014). In other words, the time series has a memory. But if a time series is non-stationary (e.g., random walk), that means the time series is unpredictable with changing mean, variance, and autocovariance. In other words, the time series does not have memory.

Augmented Dickey-Fuller (ADF) is actually a transformed autoregressive model. Below is the formula of ADF test for p-th order autoregressive process:

$$y_t = \mathrm{c_t} + \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta_i \, \Delta y_{t-i} + e_t$$

What I used to measure sustainability is the value of p in this formula. The value for p means the number of the lag differenced term Δy_{t-i} in needed to capture the serial correlation in time series y_t. $\Delta y_{t-i}$is the differenced term of the time series y_t and equals to $y_{t-i} - y_{t-i-1}$. For example, given a time series y_t indicating daily volume of tweets, if p = 6, then adding 6 lag differenced terms captures the dynamics in the time series y_t. That means, tweets in the past six days can best predict the tweets for today. Simply put, the dynamics of the tweet volumes has a memory of 6 days. Since β_i follows a regular *t*-distribution, using the standard *t*-test and *F*-test can determine the appropriate value for p.

APPENDIX B. Granger Causality Tests Results (Chapter 3)

Table 14

Granger Causality Tests Results from Chapter 3

Independent Variable	Granger Test Dependent Variables			
	Twitter	Google Trends	Press Release	News
Daily (lag=8)				
Twitter	0.00	0.00	0.00	0.002
Google Trends	0.00	0.00	0.00	0.003
Press release	0.00	0.00	0.00	0.01
News	0.00	0.00	0.00	0.00
Events	0.00	0.15	0.59	0.55
Monthly (lag=2)				
Twitter	0.00	0.00	0.00	0.002
Google Trends	0.00	0.00	0.01	0.007
Press release	0.94	0.74	0.00	0.67
News	0.004	0.01	0.00	0.004
Events	0.02	0.07	0.68	0.002

Notes: The numbers in columns under the label "Granger Test Dependent Variables" are p-values from Granger F-tests from the independent variables to the dependent variables. The numbers for Events, which added as an exogenous variable, are p-values for the events coefficients in each estimated equation in the VAR model. The choice of lag is based on the information criteria (AIC and HQIC) of each model.

APPENDIX C. Supervised Machine Learning Model Feature Descriptions (Chapter 4)

Table 15

Supervised Machine Learning Model Feature Descriptions

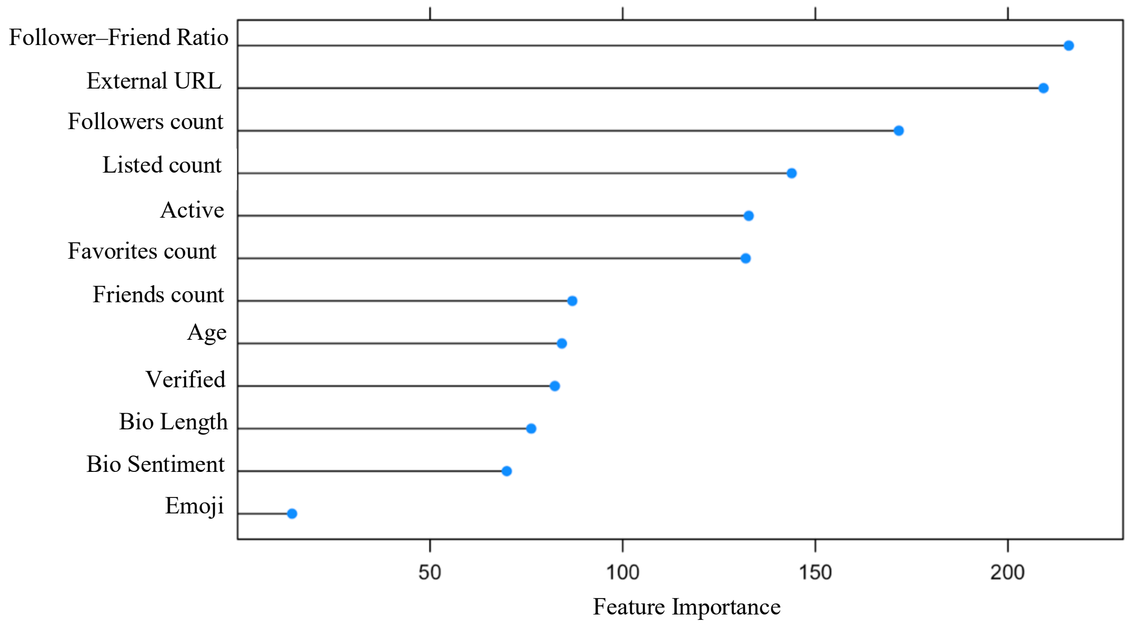
Feature	Description
Followers count	The number of followers an account has.
Friends count	The number of users an account follows.
Follower–Friend Ratio	This ratio represents a user's followers count divided by its friends count.
Favorites count	The number of tweets that a user has favorited.
Listed count	The number of times a user was added to a list by other users.
Verified	A binary variable indicating whether Twitter has officially verified an account, where a value of "1" represents the account is an officially verified account and a value of "0" represents the account is not officially verified.
External URL	A binary variable indicating if an account has a link in the profile description.
Age	The number of days since the creation of a user account.
Active	Measured by average tweets published per day. It is calculated as the ratio between status account and age.
Bio length	The number of characters used in a user's bio.
Bio sentiment	The sentiment score of a user's bio description.
Emoji	A binary variable indicating if a user's screen name includes an emoji. A value of "1" indicates the user's screen name include an emoji and a value of "1" indicates the user's screen name does not include an emoji.

Notes: The table describes the features, which is the predicting variables in the Random Forest model used to classify Twitter users. The Description column explains the metrics that I used to calculate or measure the feature.

APPENDIX D. Random Forest Feature Importance (Chapter 4)

Figure 15

Random Forest Feature Importance



Note. The value in x-axis is the quantified impact of the features. They are calculated based on the reduction of predictive accuracy when the feature is excluded from the Random Forest model. The higher the value, the more important a feature becomes in the Random Forest model.

APPENDIX E. Granger Causality Tests Results (Chapter 5)

Table 16

The Granger Causality Results for the Earth Day Event

Independent Variable		Granger Test Dependent Variables	
		Google Trends	Online News
Twitter: Political actors	→	0.03	0.15
	←	0.005 (lag=3)	0.36 (lag=1)
Twitter: News actors	→	0.001	0.004
	←	0.09 (lag=2)	0.03 (lag=2)
Twitter: Advocacy actors	→	0.001	0.02
	←	0.04 (lag=4)	0.53 (lag=3)
Twitter: Other organizations	→	0.001	0.003
	←	0.052 (negative) (lag=5)	0.04 (lag=1)
Twitter: Individual actors	→	0.001	0.004
	←	0.65 (lag=3)	0.26 (lag=1)

Notes: The numbers in columns under the label "Granger Test Dependent Variables" are *p*-values from Granger F-tests from the independent variables to the dependent variables. To select the number of lags, I run `varsoc` command in Stata. I referred information criteria AIC, HQIC and SBIC to select the number of lags.

Table 17

The Granger Causality Results for People's Climate Movement Event

Independent Variable		Granger Test Dependent Variables	
		Google Trends	Online News
Twitter: Political actors	→	0.004	0.07
	←	0.05 (lag=2)	0.92 (lag=2)
Twitter: News actors	→	0.001	0.001
	←	0.05 (lag=3)	0.39 (lag=2)
Twitter: Advocacy actors	→	0.11	0.001
	←	0.01 (lag=3)	0.09 (lag=2)
Twitter: Other organizations	→	0.001	0.07
	←	0.001 (lag=3)	0.64 (lag=2)
Twitter: Individual actors	→	0.001	0.001
	←	0.001 (lag=3)	0.034 (lag=4)

Notes: The numbers in columns under the label "Granger Test Dependent Variables" are *p*-values from Granger F-tests from the independent variables to the dependent variables. To select the number of lags, I run `varsoc` command in Stata. I referred information criteria AIC, HQIC and SBIC to select the number of lags.

Table 18

The Granger Causality Results for Obama on Facebook Event

Independent Variable		Granger Test Dependent Variables	
		Google Trends	Online News
Twitter: Political actors	→	0.67	0.20
	←	0.07 (lag=1)	0.19 (lag=1)
Twitter: News actors	→	0.15	0.001
	←	0.09 (lag=1)	0.02 (lag=1)
Twitter: Advocacy actors	→	0.50	0.12
	←	0.08 (lag=1)	0.14 (lag=1)
Twitter: Other organizations	→	0.10	0.1
	←	0.06 (lag=1)	0.64 (lag=3)
Twitter: Individual actors	→	0.01	0.001
	←	0.07 (lag=1)	0.001 (lag=1)

Notes: The numbers in columns under the label "Granger Test Dependent Variables" are *p*-values from Granger F-tests from the independent variables to the dependent variables. To select the number of lags, I run `varsoc` command in Stata. I referred information criteria AIC, HQIC and SBIC to select the number of lags.

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