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Attention Strategies For Nonprofit Advocacy On Social Media: Results From A National Study Of Homelessness Nonprofits In The United States

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Abstract
This dissertation examines the effectiveness of nonprofit advocacy on social media. With nationwide data on homelessness nonprofits in the United States, this is the first to examine how the such organizations use social media, what they frequently say on social media, and how effectively they use social media in order to garner public attention. Extending Guo and Saxton's Social Media Advocacy model, I propose a comprehensive model containing three major categories that explain the level of public attention. The first category is network characteristics, which includes network size and network influence. The second category is communication strategy, which contains three subcomponents of timing and pacing, targeting, and connecting strategy. The third category is content strategy with its two elements of content richness and sentiment/tone.

Nationwide data on homelessness nonprofits in the U.S. are compiled by combining multiple data sources; 326,620 Twitter messages sent by the sample organizations are collected via the Twitter API. Data analysis consists of three phases. Phase one presents findings on the national description of nonprofit organizations in the homelessness sector and their social media adoption and use. In phase two, a series of content analyses is conducted on the Twitter messages sent by homelessness nonprofits to explore topics discussed by the organizations. The findings from the topic modeling via LDA identify seven themes that are most frequently employed by homelessness nonprofits while successfully obtaining attention from other users. The seven themes include seeking support, homeless youth, housing and care service, domestic violence, emotional dialogue, homelessness, and veterans. In phase three, the study's hypotheses are tested both at the organizational and message levels. The analysis generates the following major findings: network size, connecting strategies, informative content, and positive tone are found to be important determinants of the attention on social media both at the organizational level and message level. There may be different attention mechanisms between the organizational level and message level as some factors (e.g., public reply) are found to have a significant but different direction of relationship with attention between the two levels.

This study adds to the literature on social media advocacy by focusing on attention. The study applies Big Data approach to identify topics discussed by homelessness nonprofits, adds new factors of message strategy on "what to speak" and "how to speak", and examines the determinants of audience attention at both the organizational and message levels. The findings from this study provides critical insights for nonprofit practitioners and advocates. In order to capture public attention, nonprofit organizations should spur efforts to increase their network size on social media, speak frequently, connect with others, offer informative and image content, and speak positively with an informal tone. Another important insight for nonprofit organizations is that how much attention an organization acquires on social media depends less on the organization's resources, but more on effective use of social media. That is, no matter how small, an organization can increase awareness and drive audience attention by using social media strategically.

As homelessness nonprofits increasingly turn to social media to advocate for their constituents and homelessness issues, it is vital for nonprofit practitioners and advocates to employ effective social media strategies that make better use of their limited resources. This study will help build an evidence base for successful social media strategies, thus helping organizations influence public policy-makers, increase efforts to support their constituents, and allocate more resources to social media advocacy work.

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ABSTRACT

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Chapter 1. Introduction

The proliferation of social media has opened new possibilities for advocacy strategies among nonprofit organizations (Deschamps & Mcnutt, 2014; Guo & Saxton, 2014). The interactive and decentralized environment of social media enables nonprofit organizations to build and maintain networks with a variety of stakeholders. Furthermore, social media offer organizations the unique capacity to share information with larger audiences in real-time, allowing them to advocate for their constituents at a lower cost than traditional advocacy activities (Campbell, Lambright, & Wells, 2014; Guo & Saxton, 2014).

Scholars have shown a growing interest in the role of social media in nonprofit advocacy. A number of studies have investigated the prevalence of social media among nonprofit organizations, how they use these digital platforms for advocacy efforts, and what type of social media messages are effective in the context of nonprofit advocacy. These preliminary studies have provided a valuable foundation for understanding social media use in nonprofit advocacy. However, the existing research has almost exclusively focused on larger organizations. Given the fact that small organizations compose the majority of the nonprofit sector in the US (McKeever, 2015), it is important to include them to better represent the social media use pattern of nonprofit organizations. The previous studies also remain limited by the small sample size of data, while Big Data and the computational approach provide researchers with a new opportunity to collect and analyze large amounts of social media data. As far as is known, no previous study has employed the Big Data approach to investigate social media-based nonprofit advocacy, particularly in the homelessness sector.

This dissertation attempts to fill the gap. Specifically, I assemble and focus on a unique, nationwide dataset of nonprofit organizations that work to prevent and end homelessness. By applying Latent Dirichlet Allocation (LDA) and dictionary methodology, I then explore what topics on homelessness advocacy are frequently discussed on Twitter. Extending Guo and Saxton's Social Media Advocacy model, this study also attempts to develop a comprehensive model of social media-based nonprofit advocacy that explains the factors influencing audience attention on social media at both organizational and message levels.

Nonprofit organizations focusing on homelessness have rapidly utilized social media as a tool to communicate with their stakeholders (Creedon, 2014). Moreover, the recent success of homelessness advocacy campaigns (e.g., STREATS, Project 50/50, and We Are Visible) has shown the potential of social media by which homelessness organizations are able to reach out to and communicate with a large scope of stakeholders who can come together to advocate for homeless people. As such, given the context of their constituents and stakeholders, social media platforms are particularly vital for homelessness nonprofit organizations.

In this chapter, I begin with definitions of the term "advocacy" and its uses in studies related to nonprofit advocacy. I then review the existing literature on advocacy strategies and tactics. In the following section, the current situation of social media use in nonprofit advocacy is discussed. I then explore the issue of effectiveness in using social media for nonprofit advocacy efforts and discuss attention as the primary focus of this study. The final section of the chapter discusses the purpose of the study.

1.1. Definition of Nonprofit Advocacy

Scholars have defined advocacy in different ways. Some scholars focus on policy activities. According to Jenkins (1987), advocacy refers to "any attempt to influence the decisions of an institutional elite on behalf of a collective interest" (p.297). Similarly, Guo and Saxton (2010) define advocacy as efforts to influence or change governmental policies at local or national levels. Other scholars describe advocacy as a wide range of activities in a democratic civil society for building social capital, facilitating civic engagement, and providing a public voice (Boris & Mosher-Williams, 1998). Reid (2000) viewed advocacy as individual and collective expression or activities for a cause, idea, or policy. Similarly, advocacy has also been described as an attempt to mobilize support (Mosley, 2011), achieve social justice (Mickelson, 1995), protect basic civil rights (Frumkin, 2002; McCarthy & Castelli, 2002), and effect changes in present or future practices for a group of people sharing a common interest (Ezell, 2000).

Although there is no unified definition of advocacy in the existing literature, the above studies demonstrate that the term "advocacy" can be used broadly as an umbrella for a wide range of collective efforts to influence public policy. According to the broad definition, nonprofit advocacy activities can include lobbying policy makers, monitoring and providing feedback on policy implementation, shaping public opinion through public education, researching specific legislation or social problems, facilitating public actions and mobilizations, setting agendas, and influencing elections.

Advocacy is widely regarded as an eminent function of nonprofit organizations to represent and promote the interests of their constituents and achieve organizational goals (Coates & David, 2002; Guo, 2007; Mosley, 2012; O'Connell, 1994). Organizations disseminate information to educate and inform the public on social issues to influence attitudes and to change behaviors. They may also represent rights and interests of their constituents by lobbying elected officials, litigating in the courts, or promoting a public campaign.

While advocacy activities by nonprofits have gained scholars' attention in past years, many studies (e.g., Boris & Mosher-Williams, 1998) have concentrated only on "advocacy organizations" whose core activity is advocacy. However, it is important to note the distinction between an advocacy organization and nonprofit advocacy as many nonprofit organizations may engage in advocacy activities even though that is not their primary mission. Research shows that many nonprofits conduct an array of activities that can be viewed as advocacy (Boris & Maronick, 2012), and thereby suggests that research on advocacy within the nonprofit arena should be broadened to include organizations that may not be labeled as "advocacy organizations" (Schmid & Almog-Bar, 2013). For instance, advocacy studies focused on nonprofit human service organizations (e.g., Clemens & Guthrie, 2010; Salamon, 1995; Smith & Gronbjerg, 2006; Garrow & Hasenfeld, 2014) note that these organizations, the main providers of social services, have historically engaged in advocacy on behalf of the vulnerable population they serve.

1.2. Strategies and Tactics of Nonprofit Advocacy

Scholars have attempted to identify different types of advocacy strategies. Berry (1977) proposed four advocacy strategies - litigation, embarrassment and confrontation, information, and constituency influence and pressure. Building on this work, Walker (1991) identified eight advocacy tactics: administrative lobbying, legislative lobbying, working with mass media, providing speakers, sponsoring lay conferences, litigating, electioneering, and protesting or demonstrating. Hoefer (2001), focused on human service organizations, introduced twelve tactics for influencing the regulation writing process: building coalitions with non-governmental organizations, bringing current regulations to the attention of Congress, bringing current regulations to the attention of executive branch agencies, providing information to other groups, taking changes to proposed regulations to Congress, taking changes to proposed regulations to the proposing agency, participating in public hearings, offering drafts of regulations prior to publication in The Federal Register, influencing decision-makers through the press, taking changes to proposed regulations to the White House, influencing the public through the press, and taking adopted regulations to court. More recently, Guo and Saxton (2010) propose eleven advocacy tactics: research, media advocacy, direct lobbying, grassroots lobbying, public events and direct action, judicial advocacy, public education, coalition building, administrative lobbying, voter registration and education, and expert testimony.

Scholars have also attempted to categorize various advocacy strategies and tactics into subgroups based upon the nature of each activity (e.g., Andrews & Edwards, 2004;

Gormley & Cymrot, 2006; Hoefer, 2005; Walker, 1991). For example, in a factor analysis of eight advocacy strategies, Gais and Walker (1991) characterized the inside and outside strategies; the inside strategies include those that organizations use to closely consult with political and administrative leaders, such as litigation, lobbying, and electioneering. The outsider tactics are an organization's efforts to draw the attention of the public and influence public opinion, including mass media advocacy, protesting or demonstrating, and providing speakers.

Recent work by Casey (2011) furthers this by including online advocacy activities and proposing extensive categorizations of advocacy strategies: Legal (e.g., providing expert evidence for litigation), legislative and administrative (e.g., encouraging individuals to express support specific policy through phone calls, letters, e-mails), research and policy analysis (distribution of research reports, evaluating outcomes of programs), coalition building and capacity development (creating new organizations, establishing coalitions of organizations), education and mobilization (distributing online materials to educate the public, organizing educational or cultural activities), communication and media outreach (e.g., sending letters to the editor, posting blog entries, tweets, and participating in online forums), government relations and oversight (e.g., participating in government consultation or advisory process, legislative hearing), and service delivery (e.g., implementing and disseminating a new model of service delivery). Collectively, the previous research underscores the importance of advocacy for nonprofit organizations to better support their constituents and has identified the wide range of advocacy strategies employed by nonprofit organizations.

1.3. Social Media-Based Nonprofit Advocacy

Nonprofit organizations use various social media sites to disseminate their message, gain additional attention from new viewers, seek donors and volunteers, build relationships with community members and political authorities, and produce revenue for their outreach efforts. Several terms have been used interchangeably to refer to social media, such as "Social Networking Site" (SNS), "Social Media Site," and "Social Networking Application." Scholars have defined social media as "an array of digital tools that allow people to create their stories, videos, and photos and to manipulate and share them widely at almost no cost" (Kanter & Fine, 2010, p.5), "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content" (Kaplan & Haenlein, 2010), and "sites that allow users to link to distinct profiles" (Hogans, 2008, p.252).

Similarly, Boyd and Ellison (2008) also describe social networking sites as "Web-based services that allow individuals to 1) construct a public or semi-public profile within a bounded system; 2) articulate a list of other users with whom they share a connection; and 3) view and traverse their list of connections and those made by others within the system" (p.211). Today, a number of traditional websites have incorporated social networking features, and the term social media is more broadly used to describe "any website or web-based service that includes web 2.0 characteristics and contains some aspect of user generated content" (Gruzd, Staves, & Wilk, 2012, p.2341). Examples of social media sites include Facebook, Twitter, YouTube, Snapchat, WhatsApp, Instagram, LinkedIn, Tumblr, and Google+.

Social media have engendered a new way for nonprofit advocacy to develop networks with stakeholders and influence policies (Deschamps & Mcnutt, 2014; Saxton, Guo, & Brown, 2007). Social media sites such as Facebook and Twitter provide an interactive and decentralized communication channel, enabling organizations to expand the scope of their advocacy efforts by mobilizing supporters and encouraging them to engage in advocacy work (Guo & Saxton, 2014). Such sites also provide an opportunity for organizations - no matter how small - to interact with and spread their messages to large audiences at a low-cost (Lovejoy, Waters, & Saxton, 2012). The majority of nonprofit organizations are active on social media in order to facilitate online community building, engage in fundraising and advocacy, and further their missions (Finn, Maher, & Forster, 2006; Hackler & Saxton, 2007; McNutt & Boland, 1999; McNutt & Menon, 2008).

A growing body of literature has explored the use of social media for advocacy by nonprofit organizations. The earliest studies focused on whether nonprofit organizations were utilizing social media platforms in their advocacy work (Bortree & Seltzer, 2009; Greenberg & MacAulay, 2009). For instance, Edwards and Hoefer (2010) analyzed 63 social work organizations and discovered that nonprofit organizations began to utilize social media on advocacy work. These early studies only examined the prevalence of social media, or whether advocacy organizations used these tools, but did not investigate how nonprofits used them.

More recently, nonprofit scholars have begun to explore how organizations use the digital networking tools and which organizations are more likely to adopt social media (Auger, 2013; Guo & Saxton, 2014; Obar, Zube, & Lampe, 2012; Petray, 2011). For instance, Greenberg and MacAulay (2009) studied 43 environmental organizations in Canada to determine the degree to which these organizations used social media. The authors pointed out that the majority of the Canadian organizations did not take advantage of social media to build networks or to engage their supporters; rather, they tended to use them frequently to deliver one-way messages.

Guo and Saxton (2013), who applied a framework of nonprofit advocacy strategies and tactics in offline settings to the social media context, found that a handful of tactics dominated in the 750 Twitter messages they analyzed; *Public education* accounted for 40% of all tweets, while three other tactics (*grassroots lobbying, public events and direct action, and voter registration and education*) appeared in only 15 to 18 of 750 tweets. These distinct advocacy strategies might have developed because of the characteristics of social media. While other communication tools, such as letter-writing, telephone, and email, tend to have a targeted audience, social media messages can be disseminated to an unlimited number of users. The authors point out that "such a mass approach seems to work better with indirect advocacy tactics (e.g., public education, grassroots lobbying, etc.) that aim at diffused publics; it works less well with direct lobbying and other 'insider' tactics that require a targeted approach" (p.74).

Meanwhile, communication scholars have also provided novel insights into understanding message strategies on social media (Lovejoy & Saxton, 2012; Rybalko & Seltzer, 2010; Waters & Jamal, 2011). For instance, in a study examining key communicative strategies in the Twitter messages sent by the largest 100 American nonprofit organizations, Lovejoy and Saxton (2012) identified three key communicative functions - delivering information (e.g., an organization's activities, events, news, reports or information relevant to stakeholders), building an online community (i.e., interacting or sharing with stakeholders), and calling for action (e.g., donation, attending events, and engaging in advocacy campaigns). Likewise, employing content analysis on Facebook messages from the 100 largest nonprofit organizations in the United States, Saxton and Waters (2014) categorized Facebook messages into three types: information-sharing, promotion and mobilization, and dialogue and community-building. They examined the relationship between these message types and the reactions of the Facebook users in the form of liking, commenting, and sharing, and found that the public is more likely to engage with organizations when they post community-building messages.

While social media are burgeoning as a new nonprofit advocacy channel, critics argue that social media may not enhance advocacy capability, but rather generate challenges to nonprofit advocacy. As not everyone is familiar with new digital technologies, social media-based advocacy may exclude some supporters who want to be engaged but do not know how to use social media (Brady, Young, & Mcleod, 2015). By the same token, not all nonprofits are able to fully enjoy the benefits that social media may provide. Smaller organizations may find it difficult to employ and maintain new communication channels due to a lack of resource capacity or digital technology fluency. Another challenge to social media utilization in nonprofit advocacy stems from doubts about the effectiveness of social media engagement with stakeholders; that is, supporters may become passive by having a false sense that online actions, such as liking or sharing an organization’s message, alone will produce definitive social change (Brady et al., 2015), a phenomenon referred to as slacktivism or clicktivism (Karpf, 2010).

Notwithstanding the potential challenges, a growing body of research suggests that social media can be incredibly useful for nonprofit advocacy in engagement with stakeholders and public awareness raising (Waters, Burnett, Lamm, & Lucas, 2009; Waters & Jamal, 2011). In effect, research has found that nonprofit organizations are using social media for advocacy purposes and seek to facilitate stakeholder engagement (see Auger, 2013; Lovejoy & Saxton, 2012; Waters & Jamal, 2011). This line of research, therefore, raises the issue of how organizations can best make use of social media in advocacy.

1.4. Effectiveness of Nonprofit Advocacy in Social Media

Nonprofit organizations have increasingly dedicated their time and money to social media. Accordingly, it has become important to understand whether these activities have an actual impact on accomplishing their missions. Evaluating the effectiveness of advocacy efforts on social media builds an evidence base for successful social media strategies, thus helping organizations influence public policy-makers, increase efforts to support their constituents, and allocate more resources to social media advocacy work.

What is effective social media-based advocacy and how can one measure it? Traditionally, it is difficult to study the effectiveness of advocacy efforts due to methodological problems involved in examining advocacy work and measuring its ultimate impact, which is often a policy change (Almog-Bar & Schmid, 2014; Hoefer, 2001, 2005; Hoefer & Ferguson, 2007; Hudson, 2002; A. Jackson, 2014; Mcnutt, 2010).

Even if one can measure the effect of advocacy work (e.g., a specific policy outcome), it is even harder to empirically observe whether the advocacy work has affected the policy outcome at all along with many other factors.

Despite these difficulties, it remains important for advocacy activities to obtain tangible results that manifest some degree of success whereby organizations can gain more support and resources for the advocacy work (Coates & David, 2002). Researchers who study nonprofits have attempted to examine the advocacy effectiveness in alternative ways by proposing intermediate indicators for advocacy effectiveness (Donaldson & Shields, 2008; J. McNutt, 2011; Mcnutt, 2010). Examples of such indicators include building networks and coalitions (Andrews & Edwards, 2004; Lin, 2002; Rochon & Meyer, 1997), and raising public awareness (Brown, Ebrahim, & Batliwala, 2012; Johansen & Leroux, 2012; Teles & Schmitt, 2011).

Although social media based-advocacy cannot be free from the abovementioned limitations, social media provide a new research opportunity to measure the immediate effect of nonprofit advocacy efforts through the digital platforms. For example, social media sites offer a quantifiable measurement by which an organization can get a sense of how many people may directly have access to its message; it is easy to track the number of Twitter followers or Facebook friends, users who have voluntarily chosen to connect with the organization and see its social media messages.

Furthermore, social media enable observation of real-time public reactions to a post produced by a user, providing a quantitative barometer to measure what is being heard and what is not. For instance, in the context of nonprofit advocacy, Twitter users retweet an advocacy message produced by an organization to share it on their own Twitter network, which may increase public awareness on a specific agenda that the organization attempts to disseminate. On Facebook, researchers can also measure the number of likes, comments, and shares an organization's message receives to examine the extent to which online audiences react to social media message strategies.

Marketing scholars have initially pioneered the effectiveness evaluation of an organization's social media involvement (Kimmel & Kitchen, 2013; Van Luxemburg, A., & Zwiggelaa, 2011). Hoffman and Fodor (2010) argue that a well-designed social media campaign motivates customers to spread social media messages produced by enterprises and post their experience on Twitter or Facebook, leading to increases in sales and revenue. The authors stress the importance of evaluation on the effectiveness of social media strategies and suggest proxy measures: Brand awareness (number of tweets or followers), brand Engagement (number of replies or comments), and word of mouth (number of retweets, or shares).

Public administration researchers have also recognized the importance of social media measurement for effectiveness evaluation. For example, Kagarise and Zavattaro (2017) in their case study of the City of Issaquah, Washington, provided two measures of social media impact - breadth and depth of public engagement with the social media content of the city. They used the number of Twitter followers as a breadth indicator of organizational awareness among the citizens; and considered the number of visits, comments, and replies to the city’s social media account as the depth of public engagement.

In nonprofit literature, there have been several studies of what types of social media messages were effective (Saxton & Waters, 2014a; Swani, Milne, & Brown, 2013). For instance, Saxton and Waters (2014b) analyzed 1,000 Facebook posts from the 100 largest non-educational nonprofit organizations. They focused on liking, commenting and sharing on Facebook as a proxy measure of the engagement. The study found community-building and dialogue messages achieved more public engagement - likes and comments – than did information sharing. The authors highlighted evidence-based expectations for the potential of social media messages to bolster stakeholder engagement.

In the context of nonprofit advocacy, similar claims have been made by studies on how well advocacy organizations are using social media for facilitating stakeholder engagement (Obar et al., 2012), and what types of messages drive public reaction (Saxton, Niyirora, Guo, & Waters, 2015). Obar, Zube and Lampe (2012) surveyed 169 members of 53 advocacy organizations in the United States and asked about benefits of social media for advocacy work. The study participants highlighted social media's ability to "create awareness of organizational goals, messages, and strategies" and "opportunity to reach a new population, educate them, and turn them into engaged voters" (p14). While this work was limited in that it only relied on survey data and did not empirically measure the effect of social media-based advocacy, it provided considerable contribution to the knowledge base on how to observe the effectiveness of social media-based advocacy activities. These studies espouse the considerable potential of social media in nonprofit advocacy, implying advocacy groups can achieve significant and active engagement from stakeholders if social media are effectively used based on evidence-based knowledge.

One important question regarding the return on organizational investment on the social media platforms is what users' reaction (i.e., liking, comments, and sharing) indicates. Although the scholars cited below have used different terms to conceptualize these individual involvements in responding to and distributing organizational messages on social media, they demonstrated that organizations seek to invest in social media to secure 'engagement' from stakeholders: *Public response* (Saxton & Waters, 2014b), *audience engagement* (Saxton et al., 2015), *follower engagement* (Kagarise & Zavattaro, 2017).

However, in some cases, users' reaction is merely seen as a psychological state rather than engagement. In the nonprofit advocacy context, engagement refers to "individual efforts toward collective action in solving problems through our political process" (Diller, 2001, p.7), and has been measured by active individual participation in diverse activities, such as contacting officials, campaigning, protesting, petitioning, and boycotting. In this view of engagement, liking or sharing a message on social media is a clicking behavior that may be a means to civic engagement but is not the engagement itself.

Thus, how can liking and sharing be understood if not engagement? It is true that an advocacy organization wants to have its messages viewed, liked, and shared by other users who are current and potential supporters of the organization. They want what they say on social media to be heard in order to motivate audiences to further engage in advocacy activities. Therefore, I turn my focus on capturing attention as a means to address the effectiveness of investing in social media for nonprofits advocacy goals.

1.5. Focusing on Attention to Organizational Messages

Reasoned Action Theory, originally developed by Fishbein and Ajzen (1975), assumes that an individual's behavior is determined by the person's behavioral intention, and the intention to perform or not perform the behavior is influenced by his or her attitude toward the behavior. Within the nonprofit advocacy context, this framework provides an important implication. Getting a person to participate in an advocacy campaign will involve getting the person to have a positive attitude toward the campaign, and thus instill an intention to act. The first step to influence individuals' attitudes toward the campaign is to capture their attention on what the campaign says. For instance, on social media, the messages of advocacy organizations are valued only when their messages catch users' attention.

In general, attention refers to psychological engagement on a particular object (Davenport & Beck, 2001). In social media settings, the given object can be understood to be social media messages. Guo and Saxton (2018) define public attention in the context of nonprofit advocacy on social media as "the extent to which multiple audience members (individuals and organizations) react to the messages sent by an organization on its social media platform(s)" (p.8). The volume of attention on social media supports the determination of worthiness of its messages. To be specific, when an organization's social media garners higher levels of attention, the messages will be more likely to be influential (Kaplan & Haenlein, 2010). In a related manner, higher levels of audience attention can also increase the opportunity to influence a person's attitude toward the causes and to create an intention to act.

Acquiring attention through its own social media platforms can also benefit advocacy groups in controlling the framing of causes or issues. Traditionally, the mass media had monopoly power on public attention, which they could exploit to frame policy issues (Gitlin, 1980; Meyer, 1995). With the emergence of alternative media such as Twitter and Facebook to attract public attention, nonprofit organizations can offer and diffuse their preferred framing to large audiences (Tufekci, 2013). If they can generate sufficient attention, the nonprofits' messages may become influential and result in tangible advocacy outcomes.

At the same time, because the digital world provides individuals and organizations with a myriad of means to generate information, competition for public attention has intensified. Herbert Simon (1971) pointed out "in a knowledge-rich world, progress does not lie in the direction of reading and writing information faster or storing more of it. Progress lies in the direction of extracting and exploiting the patterns of the world so that far less information needs to be read, written, or stored" (p. 40). Therefore, an organizational message must compete with many other voices on the online communities to grab and hold the attention of the public.

In sum, advocacy messages on social media must be strategically utilized to acquire public attention by competing effectively within the large virtual public sphere of political social and other causes. As of now, only a single study has attempted to build an explanatory model that theorizes the relationship between social media-based nonprofit advocacy strategies and the level of attention received. Guo and Saxton (2018) analyzed 219,915 Twitter messages produced by 145 nonprofit organizations to investigate what factors are associated with the level of attention an organization receives. Using retweets and favorites as proxy measures of public attention, they found that public attention is significantly associated with organizational characteristics and behaviors on Twitter, such as network size on Twitter, tweet frequency, and connecting functions (e.g., hashtags and retweeting).

My dissertation, extending Guo and Saxton's Social Media Advocacy model (2018), attempts to establish a comprehensive model of social media-based nonprofit advocacy that explains what organizational factors and message strategies determine the level of audience attention.

1.6. Social Media-Based Advocacy in the Homelessness Sector

My dissertation focuses specifically on the homelessness sector. The majority of nonprofits serving the homeless are human service providers, focusing their resources on the provision of social services such as housing, job training, and physical and mental health services. These organizations often address policy issues related to poverty and homelessness for their clients, who, in most cases, lack a voice in the policy making process, and thus have little leverage to improve the problems and conditions they face (Culhane, 1995). For this vulnerable population, nonprofit organizations may stand as "the only potential voice to address social welfare issues related to homelessness that have been ignored or even exacerbated by private and public sector" (Wood, 2018, p2).

Therefore, advocacy is a core component of their mission to protect social rights and enhance the quality of life for people experiencing homelessness.

For nonprofit organizations serving the homelessness, social media can be an effective tool to communicate with their constituents and stakeholders. Individuals experiencing homelessness have fewer access to personal and social resources, resulting in their marginalization. Given their life context, social media may provide a new channel to society for these otherwise isolated. Research found that those experiencing homelessness use social media frequently to connect with family and friends, gain access to information and services, and build an online community (Eyrich-Garg, 2011; Le Dantec & Edwards, 2008; Yost, 2012). In a study exploring the use of the Internet and social media, Rice and Barman-Adhikari (2014) found that homeless youth frequently use social media to bridge social ties, seek support, and share ideas in a safe space with peers. Another study by Koepfler and Hansen (2012) also found that individuals, self-identified as homeless in their Twitter profile, are well connected with each other in the online community.

Nonprofit organizations focusing on homelessness have also begun to utilize social media as a tool to reach out and communicate with larger audiences to advocate for the marginalized people they serve (Creedon, 2014). The recent success of social media-based advocacy on homelessness (e.g., STREATS, Project 50/50, and We Are Visible) has further motivated homelessness nonprofits to engage in social media. For example, a social media project called Invisible People (www.invisiblepeople.tv) has encouraged individuals experiencing homelessness to use social media to make their voices heard.

The organization, who has amplified social networking for reaching out to the homeless population as well as a wide range of stakeholders, has built extensive online networks with 49,000 Facebook fans and 43,000 Twitter followers.

As Hombs (2011) points out "not only are they well intentioned homeless providers on the front lines, but the issue also impacts hospital administrators, businesses, police, judges, jailers, chambers of commerce, pedestrians, and librarians" (p. xv). A wide range of stakeholders can come together to advocate for homelessness issues. Social media, therefore, have considerable potential as an advocacy tool for nonprofit organizations targeting homelessness.

While research in the field of homelessness has mostly focused on homeless individuals' utilization of social media, only a single study to date has attempted to examine the use of social media among stakeholders at an organizational level. Examining organizational social media networks in the Dallas Metropolitan Area, Jung and Valero (2015) found that homelessness nonprofit organizations are actively using social media to raise awareness of homelessness issues and engage external stakeholders. Although Jung and Valero provided a valuable first start for a better understanding of the online behavior of nonprofits, they did not examine whether such behavior in fact strengthens the capacity or impact of homeless advocacy.

Considering the value of engaging a large scope of stakeholders as potential allies and supporters for homeless advocacy, research as to how best to utilize these new online communication tools and how to develop effective strategies for advocacy on social media is essential.

1.7. Purpose of Study

Scholars have shown a growing interest in the role of social media in nonprofit advocacy. In particular, Guo and Saxton's model provides a valuable foundation for understanding effective social media strategy in nonprofit advocacy. However, the results of studies remain limited due to several shortcomings -- small sample size, a focus on larger organizations that actively use social media, and examination of only limited aspects of social media strategies either at the organizational or message level.

Therefore, the purpose of this study is as follows. First, the study identifies topics frequently discussed by homelessness nonprofit organizations through an investigation of social media messages. Second, extending Guo and Saxton's Social Media Advocacy model, it presents a comprehensive model that theorizes social media-based advocacy strategies and their relationship with public attention at both the organizational and message levels.

By extending and developing a theoretical model, the study makes several contributions to the current scholarly literature on the effective strategies of social media-based nonprofit advocacy. Specifically, this study attempts to build a solid foundation for understanding the attention mechanism in social media-based nonprofit advocacy by 1) adding new factors of message strategy on "what to speak" and "how to speak", 2) examining the determinants of audience attention at both the organizational and message levels, and 3) employing Big Data with a large amount of sample data.

The findings from this study also have practical implications for nonprofit advocacy. As far as is known, this is the first study to analyze social media messages sent by homelessness nonprofits on a national scale. As homelessness nonprofits increasingly turn to social media to advocate for their constituents and homelessness issues, it is vital for nonprofit practitioners and advocates to employ effective social media strategies that make better use of their limited resources. This study will help build an evidence base for successful social media strategies, thus helping organizations influence public policy-makers, increase efforts to support their constituents, and allocate more resources to social media advocacy work.

The remainder of this dissertation is organized as follows: Chapter Two provides the theoretical framework and literature review. Chapter Three provides an explanation on methods and describes the process of data collection and analysis. Chapter Four presents the main findings from the analyses. Chapter Five discusses theoretical and practical implications of this study and provides conclusions.

Chapter 2. Theoretical Framework

Chapter Two provides the theoretical framework for the dissertation. This study focuses on attention as an immediate and intermediate indicator of the effectiveness of social media-based nonprofit advocacy. The chapter begins with a brief overview of the conceptual model. In the rest of the chapter, I then discuss in detail each of the three major components of the strategies for social media-based nonprofit advocacy. Specifically, the second section discusses network characteristics along the two dimensions of *network size* and *network influence*. The third section discusses the effects of three types of communication strategies (i.e., *timing and pacing, targeting, and connecting*) on audience attention. The fourth section presents the effect of content strategies on attention, along with the two dimensions of *richness of content* and *sentiment and tone*.

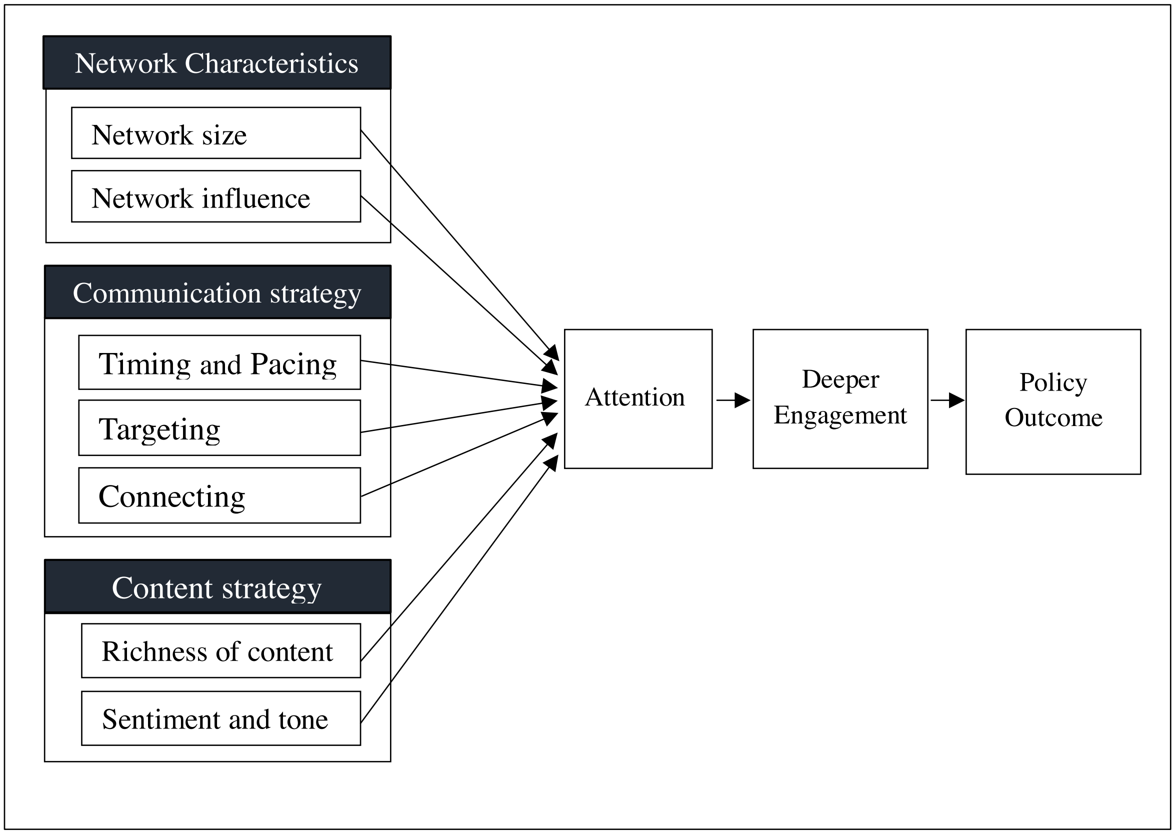
2.1. Theoretical Framework Overview

The theoretical framework was built on Guo and Saxton's Social Media Advocacy Model (2018). They proposed a four-factor explanatory model of the determinants of audience attention for organizational messages on social media. The four factors include Network Characteristics, Targeting and Connecting, Timing and Pacing, and Content. Focusing on the organizational level, the model primarily targets the technical and functional aspects of social media in its explanatory factors, such as retweeting, hashtags, mentions, public reply, URLs, and visual content in Twitter. As the first ever statistical model that attempts to explain the determinants of the level of attention on social media in the context of nonprofit advocacy, their work provides a valuable starting point for related future research. Yet, up to now, the existing literature has not yet provided clear guidance on what message strategies organizations should adopt on social media to maximize public attention.

This dissertation represents a focused effort to address this gap. By re-conceptualizing the strategies and adding new variables, I attempt to build an explanatory model to statistically test the effect of advocacy strategies on public attention obtained by nonprofit organizations. The proposed conceptual model comprises four elements – social media strategies, attention, deeper engagement, and policy outcome as shown in Figure 2.1. Although the final two outcomes, Deeper Engagement and Policy Outcome are not the focus of this study, the conceptual model posits that attention is a key prerequisite for securing the engagement that may lead to the ultimate goal - policy outcome.

In the following three sections, I introduce each component of the model along with the study hypotheses. As the study tests the model both at the organizational level and message level, each hypothesis statement is presented twice based on the units of analysis at the two different levels.

Figure 2-1. Proposed Conceptual Model on Effective Social Media-Based Nonprofit Advocacy



2.2. Attention

Building on prior research (Guo & Saxton, 2018), my study defines attention on social media as “the extent to which multiple audience members (individuals and organizations) react to the messages sent by an organization on its social media platform(s)” (p.8). People are only able to pay attention to a limited number of issues at any given time; advocacy organizations are struggling to effectively grab and hold public attention to their social media posts (Guo & Saxton, 2018). Social media provide a unique opportunity for advocacy organizations to observe public attention to their updates through the functions of liking, commenting, and sharing. These communicative functions have led advocacy organizations to think more strategically about the messages they post and consider more effective tactics for holding the attention of current and potential supporters and stakeholders.

2.3. Network Characteristics

The first category of the explanatory factors for attention on social media is Network Characteristics. According to Social Influence Theory (Kelman, 2017), audiences rely on a speaker's characteristics to determine whether a message is trustworthy.

Within the social media context, the network makes it easier to spread a message and the credibility associated with the message. Research has found that users are more likely to pay attention to social media postings generated or shared by perceived opinion leaders (Turcotte, York, Irving, Scholl, & Pingree, 2015; Weeks & Holbert, 2013). Unlike traditional leadership, opinion leadership on social media is less likely to be associated with the social, economic, or political characteristics of a speaker. Instead, network characteristics on social media play a more critical role in opinion leadership. Empirical studies have found that opinion leadership on social media platforms is largely influenced by network size (Park & Kaye, 2017; Song, Dai, & Wang, 2016; Xu, Sang, Blasiola, & Park, 2014). For example, research on nonprofits has found that the number of followers on Twitter is one of the most influential factors in determining the levels of user reaction (Bakshy et al., 2011; Saxton & Waters, 2014). Another network size factor on Twitter is the number of times an organization is included in a Twitter public list[1]. The more included in public list, the more opportunities an organization has to be exposed to broader audiences on Twitter. In recent studies, the number of public-list memberships of an organization was positively associated with user reactions (Nesi, Pantaleo, Paoli, & Zaza, 2018; Saxton & Waters, 2014b).

Network influence is also an important element of network structure on social media. In the social media network, two users build a reciprocal tie by friending each other. Within the network, they can communicate by sharing and commenting on each other's posts. In some cases, this network tie can be one-way. On Twitter, for example, one can follow a user who does not follow back. The Follow/Following Raito is often discussed as a performance indicator of a two-way network (Anger & Kittl, 2011). The higher the ratio of the network influence in the social media network of an organization, the more that users are interested in the organization's updates without needing to interact with the organization. A ratio close to 1 indicates the organization reciprocally interacts with other users. If the ratio is low, the organization is unlikely to be followed by others while following them. Differently put, network influence indicates whether an organization uses social media as a tool for broadcasting or for two-way communication (N. Jackson & Lilleker, 2011). Empirical evidence shows that a two-way communication strategy on social media drives reaction from other users. Saxton and Waters (2014)

---

[1] A curated group of Twitter accounts created by Twitter users. Viewing a List timeline will show the users a stream of Tweets from only the accounts on that List. (See more details at https://help.twitter.com/en/using-twitter/twitter-lists)

examined the relationship between different message types and the reactions of Facebook users, and found that users were more likely to engage with organizations when they posted community-building messages on Facebook. I posit here that reciprocal network structure makes it more likely for an organization to obtain attention. Based on the above, I formulate the following two hypotheses:

Hypothesis 1*: The number of followers will be positively associated with attention.*

> Organizational level: *The number of followers of an organization will be positively associated with the level of audience attention the organization receives.*
>
> Message level: *A message sent by an organization with a higher number of followers will be more likely to receive higher level of audience attention.*

Hypothesis 2*: The number of public-list membership will be positively associated with attention.*

> Organizational level: *The number of public-list membership of an organization will be positively associated with the level of audience attention the organization receives.*
>
> Message level: *A message sent by an organization with a higher number of public-list membership will be more likely to receive higher level of audience attention.*

Hypothesis 3*: The follower/following ratio will be positively associated with attention.*

Organizational level: *An organization's follower/following ratio on Twitter will be positively associated with the level of audience attention the organization receives.*

Message level: *A message sent by an organization with a higher follower/following ratio will be more likely to receive higher level of audience attention.*

2.4. Communication Strategies

Guo and Saxton (2018) proposed three communication strategies in their model and found that *tweets frequency* (Timing and Pacing) and *hashtags* (Connecting) are positively associated with the level of attention obtained by an advocacy organization. Their study showed mixed results on other elements of communication strategies. Public reply (Targeting) was negatively associated with one of the attention measures (retweets), while there was a positive relationship between public reply and the other attention measure (favorites). Retweeting (connecting strategy) showed opposite results; there was a positive relationship between retweeting others and retweets, while the connecting behavior was negatively associated with favorites an organization received. In this study, I keep all six elements of the communication strategies, as previous studies found that some represented important factors while others yielded unclear results.

2.4.1. Timing and Pacing

Timing and Pacing strategy reflects when and how often organizations should send out messages to be heard. I argue here that the higher the presence on social media, the greater the chance for an organization to acquire attention. Previous studies have found a positive relationship between message frequency and funding (Elman, Ogar, & Elman, 2000; Gross, Anderson, & Powe, 2002). The literature on social media use among nonprofit organizations also shows the volume of speech to be a powerful factor in explaining user reactions. For instance, a study on hashtags use on Twitter among advocacy organizations found that the volume of tweets was a significant variable in determining the number of retweets an organization received (Saxton et al., 2015). The findings from Guo and Saxton's work (2018) also reveal that the volume of tweets is the most powerful variable in determining the level of attention obtained by an organization. Consistent with the previous work by Guo and Saxton, this study measures the volume of speech for an organization by focusing on the number of tweets sent by the organization for a twelve-month sampling period, and posits the following hypothesis:

Hypothesis 4*: The volume of tweets will be positively associated with attention.*

Organizational level: *The volume of tweets of an organization will be positively associated with the level of audience attention the organization receives.*

Message level: *A message sent by an organization with a higher volume of tweets will be more likely to receive higher level of audience attention.*

2.4.2. Targeting

Targeting strategy refers to organizational messages that aim to communicate with specific stakeholders. By using "direct messages" on Twitter or the "wall" function on Facebook, organizations can directly and publicly speak to a specific user. For example, on Twitter, an organization can send a direct message by beginning a tweet with ‘‘@username”. The user (@username) will be able to read the tweet on his/her Twitter feed. This could encourage the message receiver to respond to the tweet and pay attention to the organization's future tweets. Lovejoy and Saxton (2012) named this type of function on social media as ‘‘public reply messages’’. Research has found that nonprofit organizations often send public reply messages (Lovejoy & Saxton, 2012; Guo & Saxton, 2018).

Based on social exchange theory and signals trust and intimacy, Guo and Saxton (2018) claim that targeting strategy triggers an obligation or motivation to respond to the communication. As mentioned above, however, the results of their study revealed a mixed result on the relationship between public reply and the level of attention. Therefore, it is necessary to retest the hypothesis with a more rigorous model.

Hypothesis 5: *The targeting strategy (public-reply) will be positively associated with audience attention.*

> Organizational level: *The number of public-reply messages of an organization will be positively associated with the level of audience attention the organization receives.*

Message level: *A public-reply message will be more likely to receive higher level of audience attention.*

2.4.3. Connecting

The next factor that may affect the level of audience attention is inclusion of a connecting element on social media content. Previous research has found that nonprofit organizations are more likely to use a one-way communication strategy despite the opportunity for two-way interaction on social media (Auger, 2013; Rybalko & Seltzer, 2010; Saxton & Waters, 2014b; Waters & Jamal, 2011; Xifra & Grau, 2010). This indicates that nonprofit organizations may use social media in an ineffective way. Therefore, it is necessary to investigate whether the broadcasting type use is effective in acquiring attention. In fact, recent literature on nonprofits provides empirical evidence that connecting elements, such as hashtags (#), hyperlinks (URLs), mentions (@), and retweeting (RT) are linked to increased public attention to the organization (see Guo & Saxton, 2018).

Hashtags, short words that follow the pound sign (#), categorize posts and help them show more easily in content searches on social media platforms. Using hashtags with advocacy efforts allows messages to spread to and garner the attention of other users on a social media platform. Saxton, Niyirora, Guo, and Waters (2015) focused on hashtags used by patient/health advocacy organizations, examining what aspects of hashtags drove retweets. They found a positive relationship between the volume of hashtags in aggregated organizational tweets and the number of retweets obtained by the organizations. Likewise, inclusion mentions (@username) in the middle of a tweet can connect to specific users or a set of users. A user can also include a hyperlink (URL) to connect to external content.

Next, as retweeting by others is an indicator of audience attention in the model, an organization's sharing (retweeting) of messages produced by other users indicates that the organization pays attention to the users. Thus, organizations can connect with others by sharing their messages. I present four hypotheses centered on Twitter tools that represent different connecting methods as follows:

Hypothesis 6a. Hyperlinks (URLs) will be positively associated with attention.

Organizational level: *The number of hyperlinks (URLs) included in an organization's tweets will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains one or more hyperlinks (URLs) will be more likely to receive higher level of audience attention.*

Hypothesis 6b. Hashtags (#) will be positively associated with attention.

Organizational level: *The number of hashtags (#) included in an organization's tweets will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains one or more hashtags (#) will be more likely to receive higher level of audience attention.*

Hypothesis 6c. Mentions (@) will be positively associated with attention.

Organizational level: *The number of mentions (@) included in an organization's tweets will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains one or more mentions (@) will be more likely to receive higher level of audience attention.*

Hypothesis 6d. Retweeting other users' tweets will be positively associated with attention.

Organizational level: *The number of an organization's tweets that are retweets of other users' tweets will be positively associated with the level of audience attention the organization receives.*

2.5. Content Strategies

The core attribute of social media is message content. Advocacy literature has examined the importance of message strategy in obtaining support for advocacy issues (Scudder & Mills, 2009; Weberling, 2012). In a social media-based advocacy context, message strategy may include what to say (*richness of content)* and how to say (*sentiment and tone).*

2.5.1. Richness of Content

Richness of content concerns whether a message contains adequate, specific and useful information. Strategic content strategy is particularly important in the social media environment in which messages are typically short. For instance, Twitter limits text in messages to 280 characters, so it is difficult to include much information in a single tweet. In the context of homelessness advocacy, this study formulates two elements of content richness – visual content and homelessness related content.

Visual Content. One way of overcoming the brevity of textual information on social media is to include visual content. For instance, Twitter allows users to add multiple media elements in a tweet, such as photos, videos, and links of a photo or video. These visual contents are greatly used by organizations in message building on social media (Saxton & Guo, 2014). For instance, findings from tourism research reveal that visual content is preferred by tourists above narrative and textual content (Munar & Jacobsen, 2014). There is also evidence of the relationship between customers' attention and visual content in marketing research (Pieters & Wedel, 2004). To capture the multiple ways of including visual content on Twitter, this study formulates the following hypotheses.

Hypothesis 7a*: Photo content will be positively associated with attention.*

Organizational level: *The number of an organization's messages that include a photo will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains a photo will be more likely to receive higher level of audience attention.*

Hypothesis 7b*: Video content will be positively associated with attention.*

Organizational level: *The number of an organization's messages that include a video will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains a video will be more likely to receive higher level of audience attention.*

Hypothesis *7c: Photo-link content will be positively associated with attention.*

Organizational level: *The number of an organization's messages that include one or more photo links will be positively associated with the level of audience attention the organization receives.*

Message level: *A message that contains one or more photo links will be more likely to receive higher level of audience attention.*

Informative Content. Another element for evaluating message quality is whether the message is informative. Psychology and communication literature have found that people are more likely to pay attention to self-relevant information from the vast amount of available information (Ingram, 1984; Petty & Cacioppo, 1979). For the purpose of public education, information message strategies are often used by communicators (Parrott, 2009). For instance, in a study analyzing 127 AIDS public advertisements, Freimuth et al. (1990) found that over half of the advertisements were informative messages to provide straightforward information. The assumption of this strategy is that individuals interested in a specific topic will pay more attention to the messages that include information they need. Dovetailing with this idea, I assume that individuals who are interested in homelessness advocacy organizations and their messages pay more attention to homelessness related messages. This leads to the following hypothesis:

Hypothesis 8*: Homelessness related textual content will be positively associated with attention.*

Organizational level: *The number of an organization's messages related to homelessness topics will be positively associated with the level of audience attention the organization receives.*

Message level: *A message related to homelessness topics will be more likely to receive higher level of audience attention.*

2.5.2. Sentiment and Tone

Scientific evidence shows that message tone drives attention and change attitude (González-Bailón, Banchs, & Kaltenbrunner, 2012; Xu & Zhang, 2018). Empirical studies on political campaigns have found that people pay more attention to negative messages than positive messages (Jordan, 1965; Lau, 1982). Experiment studies show that negatively framed messages are more persuasive than positive messages even when advocating the same position (Cobb & Kuklinski, 1997; Levin, Schneider, & Gaeth, 1998). A message that includes a negative sentiment such as anxiety, fear, or sadness, is found persuasive (Nabi, 2002).

However, the results were reversed in other settings. For example, in a study examining health-care product advertisements, a positive framing is more persuasive because an optimistic tone of a message links to an image of improving one's health (Chang, 2007). When it comes to marketing for a product, positive framing is recommended in order to minimize the perceived risk of the product (Cox & Locander, 1987; Sedikides, 1992). The homelessness issue can either be positively framed to improving the life quality for the homeless or negatively framed by highlighting the risks of this population. As this nature of homeless advocacy is similar to the health-care product case above, I draw a parallel argument and expect a positive framing message to capture greater audience attention.

Hypothesis 9*: Positive tone will be positively associated with attention.*

> Organizational level: *The level of positive tone in an organization's messages will be positively associated with the level of audience attention the organization receives.*
>
> Message level: *A positive message will be more likely to receive higher level of audience attention.*

Another element of message tone is manifested in the use of an informal tone. Online content is often written with an informal tone to build an intimate relationship with readers (Yang & Lim, 2009). Doostdar (2004) stated, ''Blogs, in general, adopt a much more informal and personal tone than what is customary in a newspaper, in part because of a perceived immediacy and intimacy in the relationship between the blogger and his or her visitors" (p. 654). In a case study on social media use among public libraries, Smeaton and Davis (2014) suggested that nonprofit organizations should regularly update social media and use an informal tone to be successful in attracting users. This argument, however, has not been statistically tested. I thus formulate the following hypothesis:

Hypothesis 10*: Informal tone will be positively associated with attention.*

Organizational level: *The level of informal tone in an organization's messages will be positively associated with the level of audience attention the organization receives.*

Message level: *A message with an informal tone will be more likely to receive higher level of audience attention.*

2.6. Organizational Characteristics

Although not shown in the conceptual model, organizational capacity attributes were included in the model testing as control variables, as they are known to be critical determinants of an organization's involvement in advocacy. Capacity refers to a set of attributes that assists or enables an organization to achieve its missions (Eisinger, 2002). Some of the most critical elements of organizational capacity cited in the literature include human resources, financial resources, and other resources such as governance structure and management policies. This study proposes two capacity-related factors: financial and human resources. A large body of research on advocacy takes for granted that financial and human resource availability enhances the likelihood of collective action (e.g., Andrews & Edwards 2004; Baumgartner & Leech 1998, Edwards & McCarthy 2004).

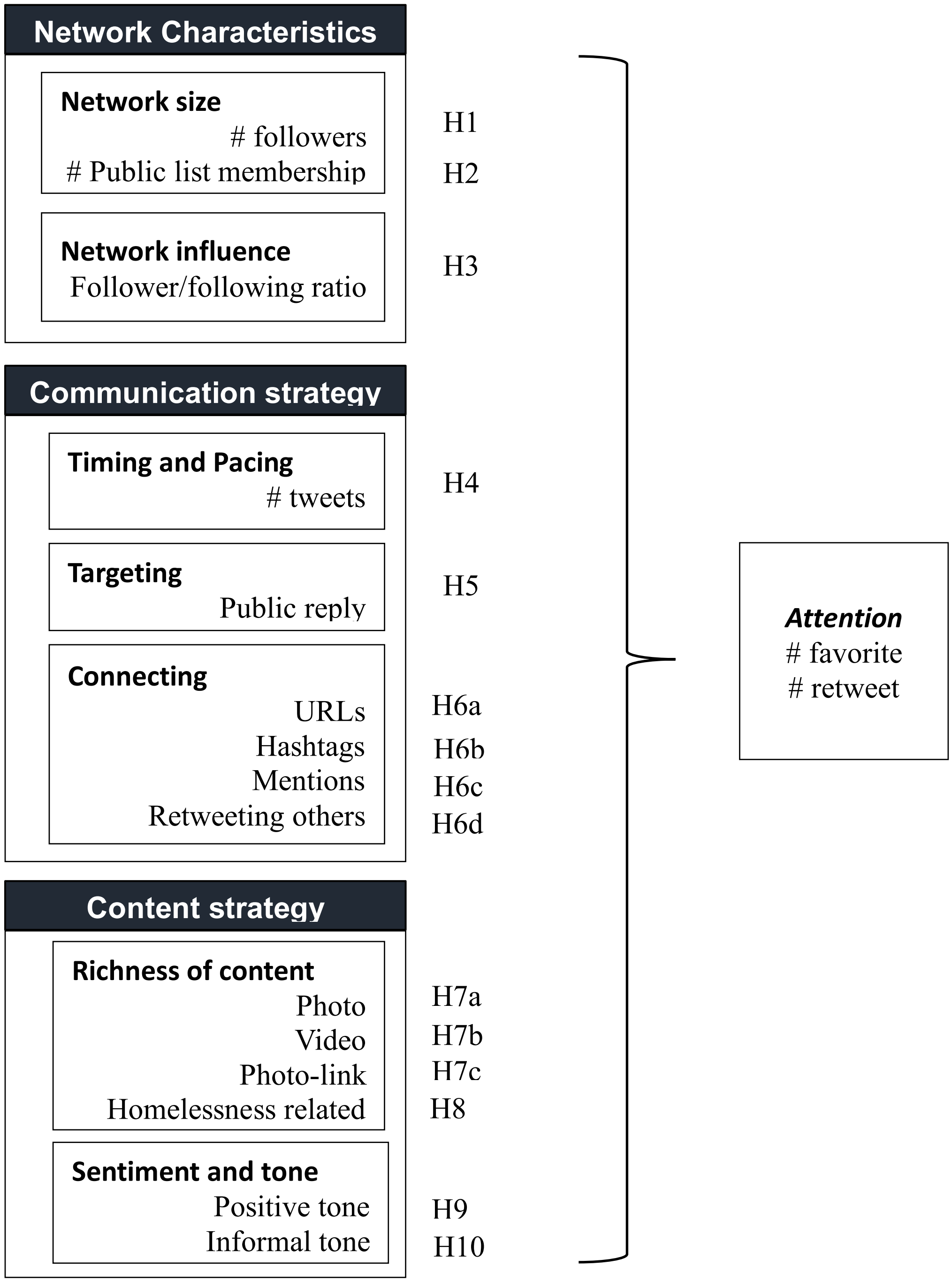
The use of social media in advocacy work is not cost-free. Organizations must invest human and financial resources in adopting and successfully operating social media. Organizations with greater capacity are better able to afford the investment. Empirical research shows that organizational capacity is a critical factor in explaining the adoption of IT technology by organizations (Corder, 2001; Gormley & Cymrot, 2006; Hackler & Saxton, 2007; J. G. McNutt & Boland, 1999; Schneider, 2003; Zorn, Flanagin, & Shoham, 2011). This, therefore, may enable larger organizations to better use social media, attracting greater attention by stakeholders and the public in the online world (Luoma & Goodstein, 1999).

Prior research has found that many organizations are unable to sufficiently utilize social media tools due to lack of human resources (Hillel Schmid, Bar, & Nirel, 2008). For instance, the American Red Cross actively uses social media to develop a relationship with stakeholders; it relies heavily on its volunteers to manage social media. Without consistent staff managing their social media accounts strategically, it is difficult for an organization to utilize these tools to their fullest extent (Briones, Kuch, Liu, & Jin, 2011).

Surprisingly, studies show that financial capacity is not likely a barrier to utilizing online tools, such as websites and social media (Nah & Saxton, 2012; Yeon, Choi, & Kiousis, 2005). In their analysis of social media adoption and use by nonprofit organizations, Nah and Saxton (2012) found no relationship between financial performance and use of social media, including presence and frequency of updates. This might be because online channels offer relatively low-cost advocacy. However, organizations' efforts to build up a larger audience size on social media must cost time and money. It is logical to think that wealthy organizations are better able to invest in financial resources to mobilize social media supporters.

In this chapter, I have provided the theoretical model to explain the determinants of audience attention in the social media-based nonprofit advocacy setting. Figure 2.2 illustrates the model with numbers of hypotheses to be tested in the following chapter, where I will provide information on the data and methods employed in the study.

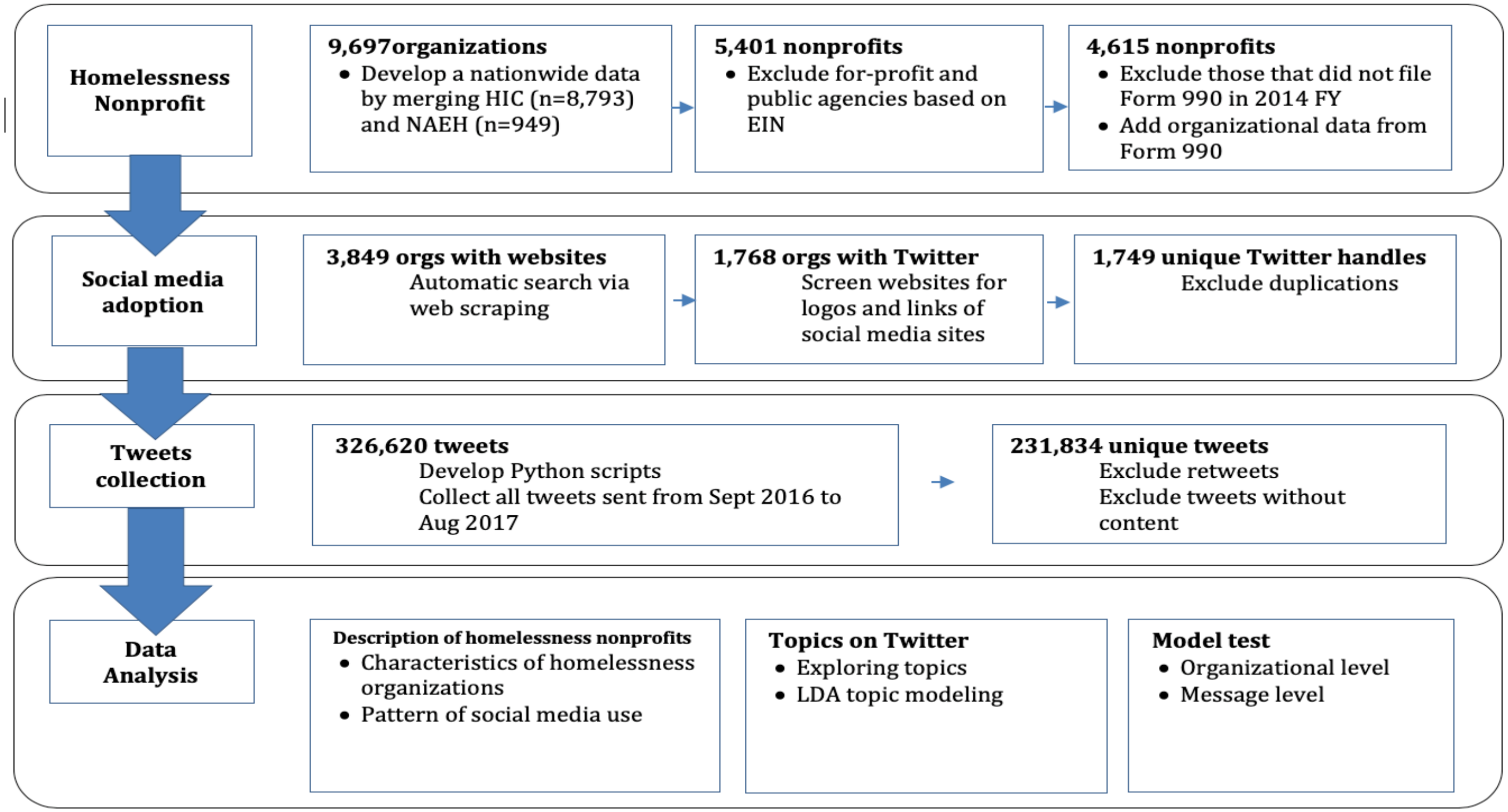
Figure 2-2. visualization of the model with hypotheses



Chapter 3. Methods

This chapter provides information on the research methodology employed in the study. Figure 3.1 illustrates the process of data collection and analysis. There are three phases of analyses in this study. The first phase is to explore the characteristics of homelessness nonprofits and their social media use. The second is to identify topics on Twitter frequently discussed by the organizations. The third phase is model testing to explain the relationship between social media-based advocacy strategies and public attention. Using multiple data, such as 2015 CoC Housing Inventory Data, GuideStar (990 Tax Form), organizations' websites, and social media sites, this study focuses explicitly on Twitter, the mainstream among many social media sites. This chapter starts with data collection with a computational approach. It then provides information on coding to develop variables. The chapter then explains specific methodologies employed in the analysis of each phase.

Figure 3-1. Data collection and Analysis Process



3.1. Data and Sample

3.1.1. Building a Nationwide Data of Homelessness nonprofits

The target population of the current study is nonprofit organizations in the homelessness sector in the United States. To identify nonprofit organizations in specific areas, researchers have widely used the National Taxonomy of Exempt Entities (NTEE) that provides a simple way of categorizing areas of nonprofit activities, paralleling Standard Industrial Classification (SIC) codes used in the private sector. However, NTEE codes impose several critical challenges for comprehensive analysis. With the simple coding of NTEE classification, each organization only has one primary code even when the organization works in multiple areas. Moreover, NTEE codes are often delayed updating miscoded organizations whose focus has changed over time (Fyall, Moore, & Gugerty, 2018). These challenges could result in misrepresenting a population for nonprofit studies.

To build a sample that better represents homelessness nonprofits in the United States, I developed a nationwide data for homelessness organizations by using multiple data sources. First, I established a nationwide list of organizations related to homelessness by merging two datasets - 2015 CoC Housing Inventory Count (HIC) and National Alliance to End Homelessness (NAEH). The 2015 HIC data, produced by US Department of Housing and Urban Development (HUD), was originally collected to obtain information on the number of beds and housing units for the homeless across the nation. The HIC data can be considered as the entire population of organizations that provide housing services ($N = 8{,}793$). In addition to housing service providers, there are other types of organizations focused more on other services or advocacy rather than providing housing services. To include those organizations in the study, supplemental data was collected from National Alliance to End Homelessness (NAEH), one of the largest national level advocacy organization that provides homelessness related organizations with education and training programs about homelessness advocacy. The NAEH data include 949 organizations that participated in the national conference of NAEH in 2016 where service providers, advocates, and public sector champions gathered to share and learn about effective homelessness advocacy strategies. I merged HIC and NAEA and removed duplicated organizations. (*N* = 9,697). I then dropped out public agencies and for-profit organizations and only selected nonprofit organizations by checking Employer Identification Number (EIN), which was obtained from GuideStar (www.guidestar.org), an online database of nonprofit organizations (*N* = 5,401).

Next, I only selected nonprofit organizations that filed Internal Revenue Service (IRS) Form 990 in 2014 Fiscal Year (*N* = 4,615). This selection method may generate some limitations. As nonprofit organizations with annual gross receipts no more than $50,000 are not required to file a Form 990, this database tends to exclude small-sized organizations. However, this approach with Form 990 enables to clearly identify the legal status of nonprofit organizations as well as to include organizational factors to be used as control variables in the final model.

3.1.2. Gathering Organizational Tweets

R scripts were written to search and scrape websites of the selected organizations automatically. Then, the website of each organization was screened for logos or links of social media accounts, such as Twitter, Facebook, Instagram, YouTube, LinkedIn, Pinterest, Google Plus, Flickr, and Vimeo.

To observe social media activities of the selected organizations, I then collected Twitter data through the Twitter Application Programming Interface (API). Among other social media platforms, Twitter is a microblogging site in which individual and organization users post 140-character messages, or tweets[2]. Twitter was selected for this study because of its widespread popularity and accessibility to posted messages. Twitter offers an easily accessible API allowing researchers to obtain the public content of a user's profile and messages. Twitter also has maintained most of the users' data available to the public unless a user sets her/his tweets to a private setting, while other social media sites, such as Facebook, have increasingly limited external access to messaging data due to privacy reason. I wrote Python scripts designed to capture all tweets produced by the selected organizations' Twitter handles from September 1st, 2016 to August 31st, 2017.

[2] Twitter upped the character limit from 140 to 280 characters in late 2017. The limit was 140 characters at the time of data collection.

3.1.3. Variables

326,620 tweets from 1,749 organizations were collected via Twitter API. The collected Twitter data include contextual information of each tweet, such as, a message sender (organizational twitter ID with the number of followers, friends, and public-list membership, time and location that presents when and where each tweet was created, and retweet & favorite count. All tweets were coded for the independent and dependent variables of the research model. Some variables were directly measured from the collected Twitter data as follows:

Public attention to Twitter messages was operationalized and measured as the total number of retweets and favorites an organization receives on their tweets.

Network characteristics. The following three network characteristics were measured once for each organization at the time of data collection, while the timeframe of the Twitter data collection is from September 1st, 2016 to August 31st, 2017. *Network size* was measured by the number of Twitter users who follow each organization's Twitter handle, and the number of public-list membership on other users' Twitter accounts. Follower/Following ratio was used to measure the degree of *network influence* in the social media network. The ratio compares the number of users subscribing to an organization's Twitter with the number of users that the organization is following.

The operationalization and measures of communication strategies followed Guo and Saxton (2018). *Timing and pacing* of the message was measured by tweeting frequency (the total number of tweets). *Targeting strategy* was operationalized with Public reply, a measure of the total number of public reply messages sent by each organization. *Connecting strategy* is operationalized with three factors: (1) retweeting, a measure of the total number of organizational tweets that are originally created by other users and retweeted by the organization, (2) Hashtags, measured as the total number of hashtags included in an organization's monthly tweets, and (3) User mentions, the total number of use mentions (@username) in organization's tweets.

For the visual content in *content strategy*, three variables were operationalized; Photos, a measure of the total number of an organization's tweets that include one or more photos; Photo and Video links, which measure the total number of an organization's tweets that include photo and video links respectively.

There are other variables in the content strategy of the model. First, for *Homelessness related topic,* I classified all tweets into two categories: homelessness-related and non-homelessness related. As there are too many tweets to manually identify homelessness related topics, dictionary methods were applied for this task. Dictionary methods are a subset of automatic content analysis techniques which have a broad goal to extract meaning from a large amount of text data. Specifically, this computational method examines text for keywords to classify the text. Dictionary method has been used by communication scholars to identify negative language in financial texts (Loughran & McDonald, 2011) and the tone of local media coverage of a presidential election (Eshbaugh-Soha, 2010). The dictionary method involves developing the classification algorithm, and thus the validity and reliability of the classification depend largely on the quality of the dictionary: it must contain words and phrases that are apocopated or unassociated with the category of interest across most cases.

The dictionary for homelessness-related word was developed based on the work by Fyall, Moore, and Gugerty (2018) in which the authors developed a dictionary of homeless related words from mission statements of 13,506 nonprofit organizations in Washington state to identify nonprofit organizations in the homelessness sector. The initial dictionary developed by the authors only analyzed mission statements and limited to one state, which might be insufficient to clarify all homelessness related tweets created by diverse organizations nationwide. To improve the dictionary of homelessness related words, I examined 1,000 randomly selected tweets from the study data and added more homelessness related words to the initial dictionary. Table 3.1 presents the final dictionary used for classification of homeless related tweets.

Table 3-1. Dictionary for scoring homelessness related tweets

Homeless related words	Score	Source
affordable housing	1	Fyall, Moore, & Gugerty (2018)
bed	1	1000 Tweets sample
domestic violence	1	Fyall, Moore, & Gugerty (2018)
emergency shelter	1	Fyall, Moore, & Gugerty (2018)
feed the hungers	1	1000 Tweets sample
group home	1	Fyall, Moore, & Gugerty (2018)
habitat for humanity	1	Fyall, Moore, & Gugerty (2018)
homeless	1	Fyall, Moore, & Gugerty (2018)
homeowner	1	Fyall, Moore, & Gugerty (2018)
homeownership	1	Fyall, Moore, & Gugerty (2018)
house	1	Fyall, Moore, & Gugerty (2018)

housing crisis	1	1000 Tweets sample
lithc	1	Fyall, Moore, & Gugerty (2018)
living on the street	1	1000 Tweets sample
low homeownership	1	Fyall, Moore, & Gugerty (2018)
low housing	1	Fyall, Moore, & Gugerty (2018)
low income homeowner	1	Fyall, Moore, & Gugerty (2018)
lowincome housing	1	Fyall, Moore, & Gugerty (2018)
lowinome homeownership	1	Fyall, Moore, & Gugerty (2018)
motel voucher	1	Fyall, Moore, & Gugerty (2018)
permanent supportive housing	1	Fyall, Moore, & Gugerty (2018)
places to sleep	1	1000 Tweets sample
psh	1	Fyall, Moore, & Gugerty (2018)
rescue mission	1	Fyall, Moore, & Gugerty (2018)
residential housing	1	Fyall, Moore, & Gugerty (2018)
section 202	1	Fyall, Moore, & Gugerty (2018)
shelter	1	Fyall, Moore, & Gugerty (2018)
sleep out	1	1000 Tweets sample
street alliance	1	1000 Tweets sample
transitional housing	1	Fyall, Moore, & Gugerty (2018)

I then systematically edited the organizational tweets to make them easier to analyze. I examined all unigrams, bigrams, and trigrams. In order to clean the tweets, I removed special characters, punctuations, and link URLs. I then stemmed all tweets to reduce the texts to their stem components. Table 3.2 is an example of tweets before and after the text cleaning. The cleaned tweets were then matched to the developed dictionary to give them a score. A tweet receives one point if it includes one word in the dictionary.

For example, the tweet in Table 3.2 would receive four points for “homeless”, “shelter”, “psh” and “psh”.

Table 3-2. Tweets cleaning and stem processing

Original Tweet
True! Many people would be homeless w/o interventions like Shelter + Care, PSH. Let s invest more $ in PSH to end h https://t.co/KxW975GGQ5
After cleaning
true mani peopl would be homeless w o intervent like shelter care psh let invest more in psh to end h t co kxw ggq

For the other two variables that measure the level of sentiment and formal/informal tone, I applied Linguistic Inquiry and Word Count (LIWC2015), a software program for counting the portion of words pertaining 90 linguistic categories. LIWC measurement schemes have been developed based on diverse textual data including Blogs, Novels, New York Times, Natural speaking, and Twitter, and rigorously tested for its reliability and external validity using different textual data (Pennebaker, Boyn, Jordan, & Blackburn, 2015).

Positive sentiment was measured with the positive emotion dictionary in LIWC that contains 620 words that indicate positive feelings such as love, sweet, and nice. Table 3.3 is an example of tweets with positive sentiment scores. The scores indicate the percentage of total words used in any given language sample, each tweet in this study.

Table 3-3. Example of tweets with positive sentiment score

Example tweet	Score
Beautiful woman with a beautiful and important message to share Thanks for helping to make ICT stronger	41.18
When you StartWithaSmile we can provide mental health counseling services to help a child recover from domestic	0

Informal tone was measured with the informal language dictionary in LIWC that contains 380 words including swear words (e.g., dam, shit), netspeak (btw, lol, thx), assent (agree, OK, yes), nonfluencies (er, hm, umm), and fillers (Imean, youknow). Table 3.4 presents examples of tweets with informal tone scores.

Table 3-4. Example of tweets with informal tone score

Example tweet	Score
Hey hey its NationalPumpkinDay Here areof the Best Savory Pumpkin Recipesvia	18.18
It s hard to get back on your feet while sleeping on the street Utahs found a solution	00

Table 3.5 presents a summary of operationalization and measures for all the variables in the model.

Table 3-5. A breakdown of all measures in the study model

Concept		Measures
Public attention		# of retweets # of favorite
Network characteristics	Network size	# of followers # of public-list membership
	Network influence	# Follower/following ratio
Communication strategy	Timing and pacing	# of tweets
	Targeting	# of public reply
	Connecting	# of retweeting others' tweet # of hashtag # of URLs # of user mention
Content strategy	Content richness	# tweets containing video # tweets containing photo homelessness related words
	Sentiment and tone	Positive
		Informal tone
Organization characteristics		Annual revenue # of employees Years of operation

3.2. Data Analysis

This study used R software to conduct a series of quantitative and content analyses. Data analysis consists of three phases: 1) descriptive analysis of homelessness nonprofit organizations in the United States and their pattern of social media use, 2) identifying topics on Twitter among the homelessness nonprofits, and 3) hypotheses testing on the effectiveness of social media based nonprofit advocacy.

3.2.1. Description of the Homelessness Sector in the US

As above mentioned, this study attempted to capture all homelessness nonprofits across the nation, and thus the collected data may allow exploring the nature of nonprofit organizations in the US homelessness sector. In this phase, I examined various aspects of characteristics of homelessness nonprofits, including the geographic distribution, age, and the structure of financial and human resources of the organizations, as well as explored the pattern of social media use of those organizations.

3.2.2. Identifying Topics on Twitter

Phase two is to explore what topics are frequently discussed by homeliness nonprofits on Twitter. Word Cloud was used as a starting point of more in-depth content analysis to summarize the collected tweets visually. This visualization technique is particularly useful to learn about the number and kind of topics present in a large body of text. To discover patterns of topical groups in the collected tweets, I conducted a topic modeling with Latent Dirichlet Allocation (LDA). LDA is an unsupervised machine learning algorithm that identifies latent topic groups with distinct probabilities in which each topic is a distribution over words or terms, and each document is a mixture of the topics. In general, topic modeling with Twitter data is difficult because every tweet is short (between 1 and 140 characters), and thus does not contain much information to discover topical groups. First introduced by Blei, Ng, and Jordan (2003), LDA has successfully been used with social media data for topic modeling (e.g., Wang, Gerber, & Brown, 2012; Kim & Shim, 2014).

The process of LDA analysis is as follows: First, I only selected tweets that had been retweeted by other users at least once to focus on the topics that had received public attention. Tweet messages from a single account (i.e., each organization) were grouped into a single document to overcome the problem of the shortness of Twitter documents, which produces a more robust model fit (Paul & Dredze, 2012). After converting the Twitter messages into a corpus, referring to a machine-readable collection of text documents, I removed noises in the document, such as hashtag (#), mention (@), URLs, stop-words (e.g., “and”, “the”), punctuations, numbers, special characters (e.g., $, %, !, and ?), white spaces between words, and non-English characters.

Next, I converted the corpus into a document-term matrix(dtm), with organizations in the rows and terms in the columns. Using the *topicmodels* package and tutorial (Xu, 2017) in R, I analyzed the obtained dtm, and obtained seven topics and the terms that co-occurred in each topic.

3.2.3. Hypotheses Test

Phase three is testing the model of the effective social media-based nonprofit advocacy. In the study, I analyzed the attention both at organizational and message levels to examine who (organization) are more likely to gain the audience attention and to understand what messages receive attention while others don't respectively.

For the test of organizational level, the collected tweets were aggregated as organizational / monthly panel data. Random Effect Regressions were conducted on the number of favorites and retweets that an organization receive each month. Fixed Effects model is often preferable for panel data analysis because it helps control for potential omitted variables that have time-invariant values. In the Fixed Effects model, however, the effects of time-invariant variables cannot be estimated as these variables are absorbed by the intercept. In contrast, Random Effects models can explain specific differences in the variables between organizations. In the study model, some time-invariant factors (i.e., follower count, public-list membership count, and following/follower ratio) are independent variables that need to be estimated.

While the organizational level analysis used aggregated panel data, the message level analysis focused more on individual tweets. To develop a more parsimonious model that better represent social media messages produced by homelessness nonprofits in the US, I used a different sample for the message level analysis; First, I removed retweets and only selected 231,834 original tweets sent out by the organizations. Then, 8,000 tweets were randomly selected by using a disproportionate stratified sampling method to ensure representativeness between organizations since they had sent greatly unequal numbers of tweets. Disproportionate stratified sampling is used when the purpose of the study is to better represent the population by including more cases from small homogeneous groups represented by only a handful of observations (Rubin & Babbie, 2016). Disproportionate sampling is common in studies of organizations where larger organizations tend to be more viable and over-represented in the studies. In this study, 1% of organizations (n= 16) sent out over 1,000 tweets for the 12 months, which accounts for over 10% of the total tweets produced by 1,576 organizations, while over half of the organizations sent out less than 100 tweets during the same period. I drew equal units from specified small subgroups a disproportionately better chance of being selected than cases from larger subgroups. First, the 1,576 organizations were assigned into ten groups based on the number of tweets they sent for the twelve-month period of this study (See Table 3.6). As the total number of tweets in the smallest strata (group1 where the organizations produced less than 11 tweets per year) is 801, I randomly selected 800 tweets from each group to equally represent the organizations. The selected 8,000 tweets were then used for the model test.

In choosing an appropriate statistical model at the message level, I considered several approaches. The two outcome variables of this study, number of retweets and number of favorites, are count variables. The nature of the variables and their highly skewed distributions make the standard Ordinary Least Squares regression (OLS) inappropriate. In the study data, both variables had an excessive number of zeros and very low variation; around 90% observations were 0 and 1. Poisson or negative binomial regression are widely used for such count data. I also ran mixed effects logistic regression models on two binary dependent variables (i.e., tweets retweeted at least once = 1, tweets not retweeted = 0 and tweets favorited at least once = 1, tweets not favorited = 0) to compare the results of different approaches and choose the best fit. The mixed effects logistic model is a useful to model binary outcome variables when data are clustered or there are both fixed and random effects. In the present case, some predictors, such as number of followers, number of public-list, follower/following ration, and organizational capacity factors, are organizational level and thus clustered.

Table 3-6. Sample of Tweets from Disproportionate Stratified Sampling

(%)	tweet frequency	Total tweets		Sample tweets	
		# tweets	# orgs	# tweets	# orgs
100	1 – 11	801	167	800	160
90	12 to 28	3,277	163	800	163
80	29 to 47	5,723	148	800	146
70	48 to 69	9,194	157	800	155
60	70 to 90	12,678	159	800	155
50	91 to 115	15,906	155	800	155
40	116 to 137	19,792	157	800	157
30	138 to 172	23,926	155	800	152
20	173 to 331	36,928	157	800	155
10	332 to 2177	103,609	158	800	153
Total		231,834	1,576	8,000	1,551

Chapter 4. Results

This chapter presents the findings from the three phases of analyses. The phase one begins by presenting various aspects of nonprofit organizations in the homelessness sector nationwide. Then I turn to the adoption and use of social media among the organizations and discuss the pattern of Twitter use. The second phase focus on topics discussed by the organizations on Twitter. By applying LDA topic modeling method, I identify ten topics produced by homelessness nonprofits on Twitter that garner audience attention. The final phase tests the hypotheses in the model of this study both at organizational and message levels to examine the determinants of attention to homelessness organizations' messages.

4.1. Description of Homelessness Nonprofit Organizations in the US

4.1.1. National Description of Homelessness nonprofits

This section summarizes some of the most salient findings from 2015 Form 990 (Federal Return of Organization Exempt Form Income Tax) to explore the homelessness field of nonprofit sector in the US. The geographic distribution of nonprofit organizations in the homelessness field varied throughout the country with a higher density in urban areas. As shown in Figure 4.1, California has the highest number of organizations (473), followed by New York (293), and Pennsylvania (250). The Northeast region had a large cluster of homelessness nonprofits, and the Southwest coast also had a cluster of nonprofits. Figure 4.2 illustrates the volume of homelessness nonprofits at a county level.

Figure 4-1. Homelessness nonprofits by state

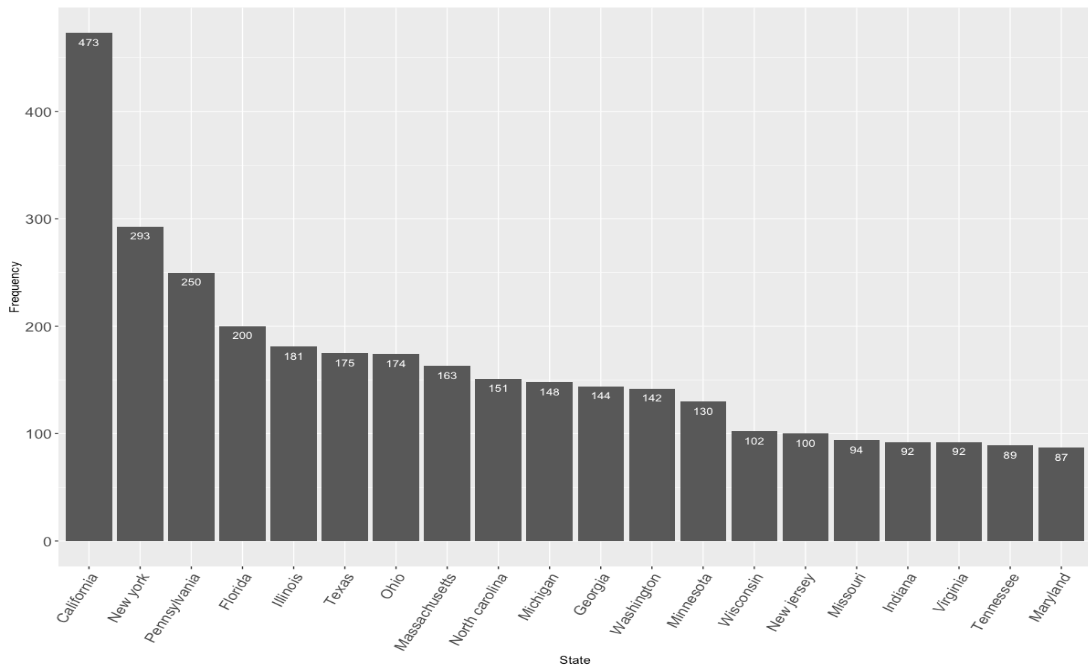
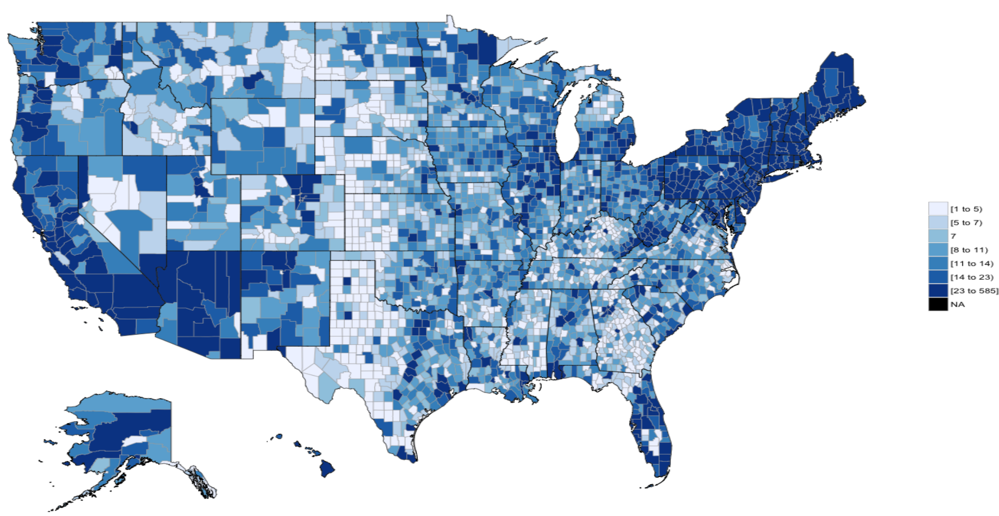
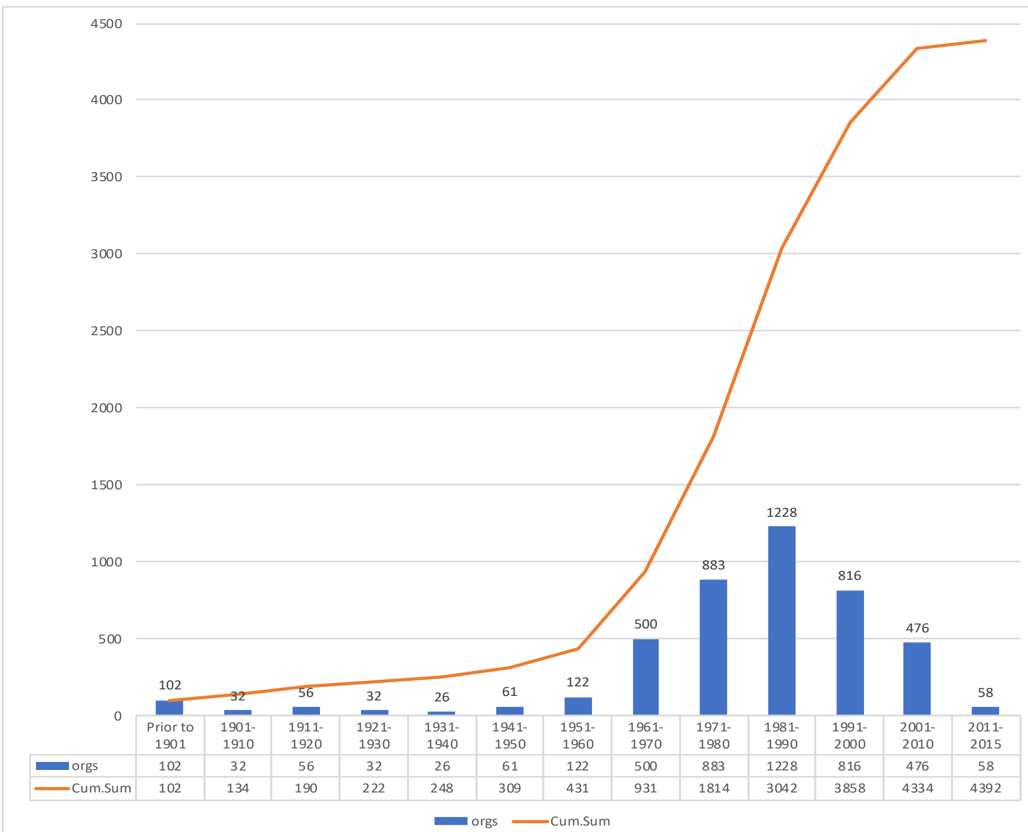


Figure 4-2. Distribution of homelessness nonprofits in the US



Organizational age. The average organizational age was, on average, 39.39 years (with a minimum of 4 and a maximum of 210, *SD* = 23.9). The founded year of the organizations ranged from 1809 to 2015 with the majority of organizations being founded after 1960 (90%). The homelessness field in the nonprofit sector was rapidly grown between the late 1970s and early 1990s, corresponding to the extraordinary increase in the number of people experiencing homelessness in those years (Burt, 1992). Figure 4.3 shows the range of years the organizations were founded.

Figure 4-3. Year the organizations were founded



	Prior to 1901	1901-1910	1911-1920	1921-1930	1931-1940	1941-1950	1951-1960	1961-1970	1971-1980	1981-1990	1991-2000	2001-2010	2011-2015
orgs	102	32	56	32	26	61	122	500	883	1228	816	476	58
Cum.Sum	102	134	190	222	248	309	431	931	1814	3042	3858	4334	4392

Financial and human resources. Table 4.1 presents the structure of financial and human resources of nonprofit organizations in the homelessness sector. As I attempted to identify all nonprofit organizations in the homeless field, the descriptive statistics provides valuable insights on how large the homelessness nonprofit sector regarding financial and human resources. The results reveal that the 4,615 homelessness nonprofits generated slightly over $44 billions in 2014FY. The descriptive analysis clearly indicates that about half of their revenues comes from service fees (48.6%). The government grant consists of 33 percent of the total revenue, followed by private giving (14.7%). The average annual budget of a homelessness organization was $9.5 million. Although the annual budget was widely spread out as indicated by the standard deviation of $80 million, half of the organizations clustered in the range of less than $1.8 million. The table also reveals the expenditure pattern of the homelessness sector. The annual expenditure in the nonprofit homelessness field is $42 billion. Not surprisingly, the homelessness organizations spend most providing services (87.9%), while the administration expenses represented about 10 percent of the total expenditure. The number of paid employees in homelessness nonprofits was slightly over 700,000, while nearly three million volunteers were involved in these organizations in 2014 fiscal year. On average, a homelessness nonprofit organization hired 155.7 paid workers and had 733.1 volunteers in 2014.

Table 4-1. Financial and human resource of homelessness nonprofits

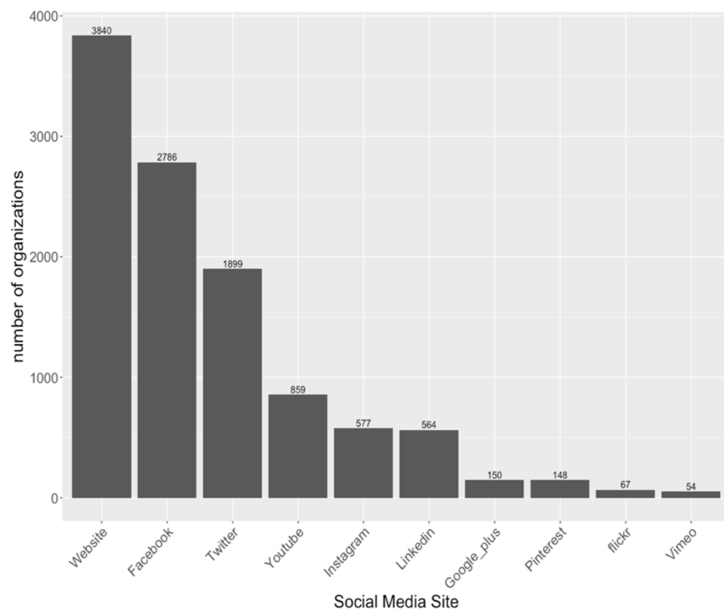
	N	Total	Mean	Min	Max
Annual revenue	**4,615**	**$44,121,047,633**	**$9,560,357**	**-$3M**	**$4,638M**
Private contribution	4,615	$6,489,995,172	$1,406,283	-$0.3M	$535M
Government grant	4,615	$14,657,629,804	$3,176,084	$0	$331M
Service fee	4,615	$21,431,296,706	$4,643,835	-$23	$3,517M
Other	4,615	$1,542,125,951	$334,155	-$7.7M	$272M
Annual expense	**4,605**	**$42,060,379,751**	**$9,133,633**	**$0**	**$4,257M**
Program service	4,600	$36,982,909,963	$8,039,763	$0	$3,872M
Fundraising	4,526	$646,188,781	$142,773	-$4	$54M
Admin	4,593	$4,432,958,403	$965,155	$0	$331M
Employees	4,561	710,053	155.7	0	37,698
Volunteers	3,987	2,923,023	733.1	0	300,400

4.1.2. Social Media Use of Homelessness nonprofits

Out of the 4,615 organizations, over 80% of the nonprofits had a website and 62.2% had at least one social media account. Slightly less than half (44.3%) had two or more social media profiles. As shown in Table 4.2, the adoption of social media sites varied across platforms. Consistent with prior studies investigating social media use among nonprofits (e.g., Lovejoy & Saxton, 2012; Asorwoe, 2017), Facebook (60.3%) and Twitter (38.3%) were two most widely used social media platforms. Although Facebook was the most popular platform in the sample of the current study, Facebook data were less accessible due to its privacy policies at the time of writing. Hence, this study analyzed Twitter data to examine social media usage as a nonprofit advocacy tool.

Table 4-2. Social media platforms adopted by Homelessness nonprofits

Social Media	Frequency	(%)
No account	1,745	37.8
Have accounts	2,870	62.2
1	827	17.9
2	746	16.2
3	670	14.5
4	422	9.1
5	149	3.2
6	50	1.1
7	6	0.1
Total	4,615	100



Adoption of Twitter In the sample of the current study, less than half of the organizations (38.3%) had a Twitter account (*n* = 1,899), whereas prior empirical studies reported that majority of nonprofit organizations used Twitter: for instance, 73% of top 100 US nonprofits (Nah & Saxton, 2012), 80% of 188 advocacy organizations rated by Charity Navigator (Guo & Saxton, 2014), and 99% of National Health Council's 105 member organizations (Saxton, Niyirora, Guo, & Waters, 2015). It is plausible that previous studies focused only on larger organizations, resulting in selection bias, and perhaps smaller organizations are less likely to have a twitter account. As the current study used rigorous sampling methods in order to secure a more representative sample as compared to prior studies, 38% of Twitter adoption may more accurately reflect the true use of Twitter among nonprofit organizations. The following analysis supports this conjecture. Table 4.3 contains the result of a logistic regression exploring a significant relationship between organizational capacity and Twitter adoption; older and larger organizations regarding human resources are more likely to have a Twitter account. Interestingly, the financial capacity reveals a significant and negative relationship with Twitter adoption, which indicates organizations with a lack of financial resource capacity may be motivated to adopt social media to look for resources at a lower cost.

Table 4-3. Correlation between Organizational characteristics and Twitter Adoption

	N	Mean	Median	Logit Regression (*B*)	p-value
Organizational Age	4,392	37.39	33	.012	.000***
Number of employees	4,561	155.7	36	.000	.000***
Number of volunteers	3,987	733.1	75	.001	.000***
Annual revenue	4,615	$9,560,357	$1,825,866	-.007	.000***

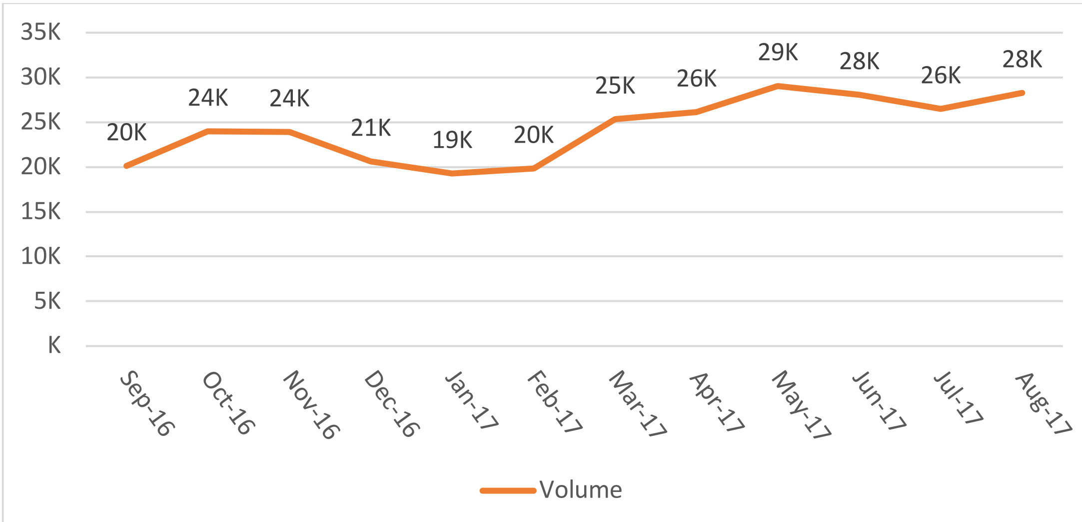
Pattern of Twitter Use. Out of the 1,899 nonprofits that have a Twitter account, 299 organizations were not active during the period of data collection[3] and there were 24 duplicated Twitter handles[4]. The remaining 1,576 organizations sent a total of 290,984 tweets over the constructed one-year period. Each month, they sent out over 20k tweets.

[3] Their Twitter handles were suspended, deactivated, or they did not send a tweet since September 2016.

[4] Some organizations were sharing a Twitter handle for some reasons. For example, DePaul Community Services and Living Opportunities of DePaul are different organizations, yet under the same umbrella organization, Depaul. @heartlandhelps was also used by four organizations, each of which is an independent nonprofit organization but belongs to Heartland Alliance. In such cases, only the umbrella organizations were selected to be include in the analysis.

The monthly volume has slightly been increased over the twelve-month period, which indicates that homelessness organizations are actively and persistently sending out messages on Twitter. (See Figure 4.4).

Figure 4-4. Total volume of tweets by month



Not surprisingly, the organizations sent more of their tweets on weekdays (see Figure 4.5). This pattern is common among organizations both in business (Wasserman, 2012) and nonprofit sector (Guidry, 2013). Similarly, the time they sent tweets were focused on working hours between 9 am and 5 pm (see Figure 4.6).

Figure 4-5. Distribution of days that tweets were sent

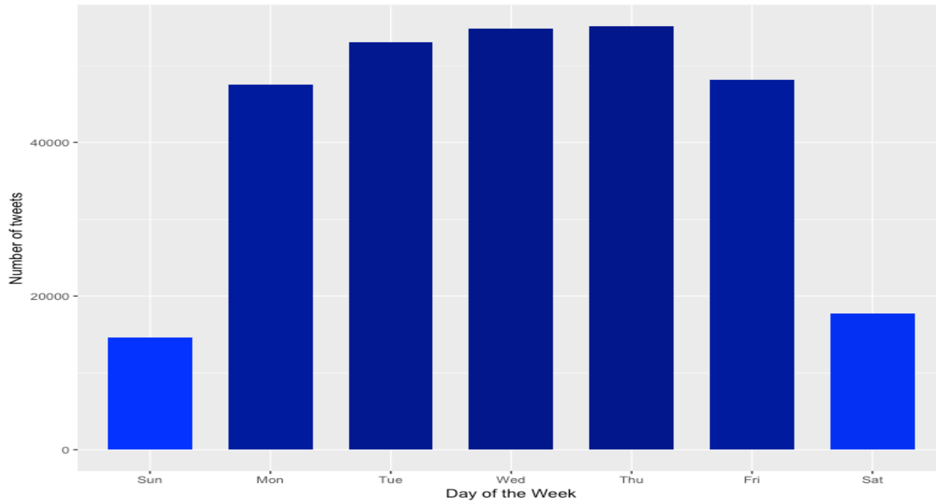
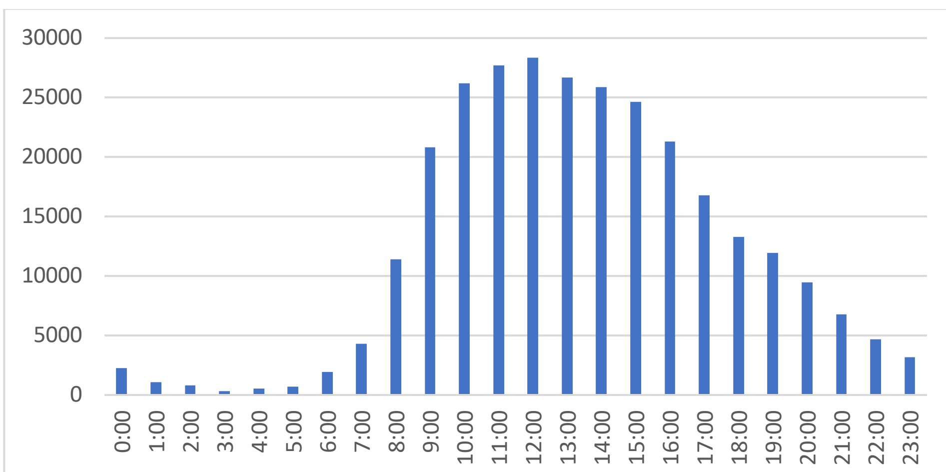


Figure 4-6. Distribution of times that tweets were sent



4.2. Identifying Topics on Twitter

Among all 290,984 tweets that 1,576 homelessness organizations produced, 59,150 were retweeted messages that the organizations re-posted tweets sent by other users. I excluded the retweets to better examine organizational messages that the homelessness nonprofits had originally sent out on Twitter. Figure 4.7 shows a word cloud based on the 231,834 original tweets, presenting top 50 popular words in the organizational tweets. The larger the word, the more frequently it appeared in the organizations' tweets. The organizations appear to frequently use Twitter as a conversation tool in speaking to the target audience. The most frequently used words include thank, help, support, homeless, day, today.

Figure 4-7. Top 50 popular words in 231,834 tweets

Descriptive statistics. As shown in Table 4.4, out of the 231,834 organizational tweets, 32 percent were retweeted, and half of them were favorited by others at least once. One in three tweets contains mentions or hashtags, while over three-quarters of the tweets include a hyperlink that provides access to additional document or Web page when clicked by users.

Table 4-4. Characteristics of the tweets sent by homelessness nonprofits (n= 231,834)

	Frequency	%	min	max
Retweeted by others	74,051	31.9%	0	1,128
Favorited by others	115,501	49.8%	0	3,972
Tweet with Hashtags	82,475	35.6%	0	12
Tweet with mentions	61,920	26.7%	0	10
Tweet with hyperlink	177,965	76.8%	0	4
Tweet includes photo	40,330	17.4%	0	1
Tweet includes photo link	3,267	1.4%	0	1
Tweet includes video	697	0.3%	0	1
Tweet includes video link	2,653	1.1%	0	1
Total tweets sent	231,834	100%		

Table 4.5 presents the top 10 popular hashtags sent by homelessness organizations on Twitter. The most popular hashtags used by homeless organizations were #givingtuesday (1,866), followed by #homeless (1,286), #homelessness (1,213), and other homelessness related words. This indicates that homelessness nonprofits use hashtags to ask donation (#givingtuesday), increase awareness of homelessness-related issues (#endhomelessness, #mentalhealth, #domesticviolence, and #veterans) or campaigns (#dvam2016).

Table 4-5. Top 10 popular hashtags (#) on Twitter

Hashtags	Freq	Example tweet
#givingtuesday	1,866	Margarita, Kimberly, and Yomary shared their #CharitiesSelfie with us! Have you done yours? #GivingTuesday https://t.co/OSoVsXN3Lx
#homeless	1,286	#HousingFirst makes a difference! #LNK 1 of 30 communities awarded #SAMSHA grant to address chronic #homelessness https://t.co/UCmxd8g8wX
#homelessness	1,213	#poverty increases the likelihood of poor health & #homelessness. @CFHNYC #HomelessMemorial @DrishaInstitute @UrbanPathwaysNY
#endhomelessness	1,073	"It takes expanding and providing more diverse housing options" -Raysa Rodriguez #EndHomelessness https://t.co/a5kSV9TqB9
#mentalhealth	1,052	May is Mental Health Awareness Month! Join the conversation to learn, share, advocate and more! #mentalhealth
#dvam2016	941	10 Ways to Support Domestic Violence Awareness Month in #FrCoKS. #OttawaKS #DVAM2016 https://t.co/MHcn9BvKU9 https://t.co/wPdSao2DVg
#affordablehousing	904	Lack of #affordablehousing is a big reason why NYC's #homeless crisis has reached a record high. We need to do more: https://t.co/h8ydQfQZZv
#domesticviolence	824	#DomesticViolence is a pattern of abusive behavior which one person gains &maintains power &control over another person in the relationship.
#veterans	674	Listen to a Vietnam Veteran's story of how ASH helped him. #veterans #heroesandhope https://t.co/IZfdX6NnV0
#dv	662	Candlelight vigil Wed eve to honor victims & survivors of #DV in #OttawaKS #DVAM2016 https://t.co/7TXuSFdoFa https://t.co/pqV5Gsq7ym

Mention function (@) is useful to be connected with other users. The most popular mentions were @youtube (966), followed by @ccdc (476), and @bankofamerica (292) as shown in Table 4.6. It is likely that @youtube were automatically added to organizational tweets when they shared YouTube videos on Twitter. Similarly, @abc and @nytimes were added when their news articles shared by organizations. Interestingly, organizations use their own username ((@ccdc, and @ucmalex) with other usernames or hashtags on Twitter so that other users can easily find and connect to them. Mention function was also used to directly speak to their stakeholders (@BankofAmerica, @sararoc, @purplepurse).

Table 4-6. Top 10 popular mentions (@) on Twitter

Usernames	Freq	Example tweet
@youtube	966	Heath's Story of Surviving Military Sexual Assault #RapeCulture #weareheretotalkaboutit https://t.co/zc2GfzP2Xw via @YouTube
@ccdc1ofkind[5]	476	@DCDHCD and @CCDC1ofakind agrees that reducing homelessness is a goal in our beloved city! https://t.co/2nuq61YKTk
@bankofamerica	292	Thanks @BankofAmerica for choosing Samaritan Place as a recipient of the Basic Human Needs Grant! You are helping u https://t.co/CfttEfIf2D
@amazonsmile	250	Cyber Monday shop @AmazonSmile, and Amazon will make a donation to the Center for Family Resources! https://t.co/WjIfAOEwVZ

[5] Community Connections, a nonprofit organization serving vulnerable individuals, families, and children residing in DC. The mention @ccdc1ofakind was used mostly be Community Connections with other hashtags and mentions to connect other users to themselves.

@nytimes	166	For those trying to stay safe in the path of #HurricaneHarvey, while #homeless -our thoughts are with them. https://t.co/A4onY9ul4C @nytimes
@ucmalex	165	Thx everyone don8ng backpacks 2 supply our #MountVernonKids 4 school success! EZ 2 shop @UCMAlex @amazon #Wishlist: https://t.co/lNKW0tOAbc
@abc	161	Man's story of helping homeless man is inspiring, heartbreaking https://t.co/qVULTpb0Gc via @ABC7NY
@amazon	158	#fathersday2017 is this Sunday! @amazon will give us part of the proceeds from purchases made through this link: https://t.co/kDU9lDxH6R
@sararoc	150	@SaraRoc05191903 Thank you for all the recent likes and retweets, Sara. May you have a blessed weekend. https://t.co/QzQl48ABeJ
@purplepurse	149	We're involved in the @PurplePurse Challenge and out to win $100,000 for our cause. Learn more at https://t.co/PEbO0XjLqN

As mentioned above, two in three organizational messages were not retweeted by others, while some tweets were retweeted over multiple times. Table 4.7 and 4.8 present top 10 tweets that were most retweeted and favorited respectively.

Table 4-7. Top 10 most retweeted tweets

Tweets	# retweet
#Onthisday 1973, the last combat troops left Vietnam. To all who served, thank you for your service and welcome home 🇺🇸 #VietnamVeteransDay 	1128
Thank you again @DearEvanHansen for the sold out special performance on Sunday! Here's @BenSPLATT's curtain speech! #forposterity	756
Inside our "Goodie Bags" for kids coming to our Children's Christmas Celebtation ... @Nutiva's O'Coconut bites	752
.@MiaYim showed domestic violence survivors everywhere you can accomplish your dreams. Retweet to congratulate her.	614
More than 58,000 lost their lives during the Vietnam War. Join @GarySinise and help keep the promise The Wall was built on – never forget.	562
Thank you to #ChrisMartin from @coldplay for visiting us down at #227Bowery and checking out our arts program for our homeless community!	544
Help Houston and all those affected by Hurricane #Harvey by giving through the United Way Harvey Recovery Fund.	507
Have you taken the vow to end #domesticviolence? Find out why @DaveNavarro has #PutTheNailinIt & join today:	502
When states like Mass. & Ky. tried a health care #SkinnyRepeal in the past, premiums rose & insurers fled	384
We welcome members of #RollingThunder to Washington, D.C. They ride for those who can't. Thank you for visiting and honoring our heroes	359

Table 4-8. Top 10 most favorited tweets

Tweets	# favorite
Thank you again @DearEvanHansen for the sold out special performance on Sunday! Here's @BenSPLATT's curtain speech! #forposterity 	3972
Thank you to #ChrisMartin from @coldplay for visiting us down at #227Bowery and checking out our arts program for our homeless community!	1788
Thank you @Lin_Manuel. Long-term recovery is crucial after the water recedes, we will be there. Support through don	1441
#Onthisday 1973, the last combat troops left Vietnam. To all who served, thank you for your service and welcome home #VietnamVeteransDay	1403
More than 58,000 lost their lives during the Vietnam War. Join @GarySinise and help keep the promise The Wall was built on – never forget.	1216
Help Houston and all those affected by Hurricane #Harvey by giving through the United Way Harvey Recovery Fund.	986
.@MiaYim showed domestic violence survivors everywhere you can accomplish your dreams. Retweet to congratulate her.	926
We welcome members of #RollingThunder to Washington, D.C. They ride for those who can't. Thank you for visiting and honoring our heros	924
Have you taken the vow to end #domesticviolence? Find out why @DaveNavarro has #PutTheNailinIt & join today:	847
Clock is ticking. Bid now to support HELP USA s housing & services: https://t.co/niMxheQKxG @MariaCuomoCole @mr_kennethcole @annelk2 @Guffj	711

Content analysis on Tweets that drive attention. In order to more closely examine the organizational tweets that have received public attention, I conducted a content analysis with 74,051 tweets that were retweeted by other users once or more, which took 31.9% of the all collected tweets.

Figure 4-8. Word Cloud of messages retweeted by others once or more (n=74,051)

Among 74,051 tweets in the sample, I analyzed the most popular 20 unigram and bi-grams (see Table 4.9). The most popular single word in the sample tweets was support (3,962), followed by day (3,768), join (3,456), and community (3,062). Not surprisingly, homelessness related terms were frequently used in the tweets that had gained attention such as, homeless, housing, people, homelessness, youth, children, program, families, and health. The analysis of bi-grams provides contextual information by showing co-occurred two words in the document. The result shows that homeless related topics were highly retweeted by other users. The most frequently used pairs of words were Domestic Violence (896), followed by Affordable Housing (501), and Mental Health (473).

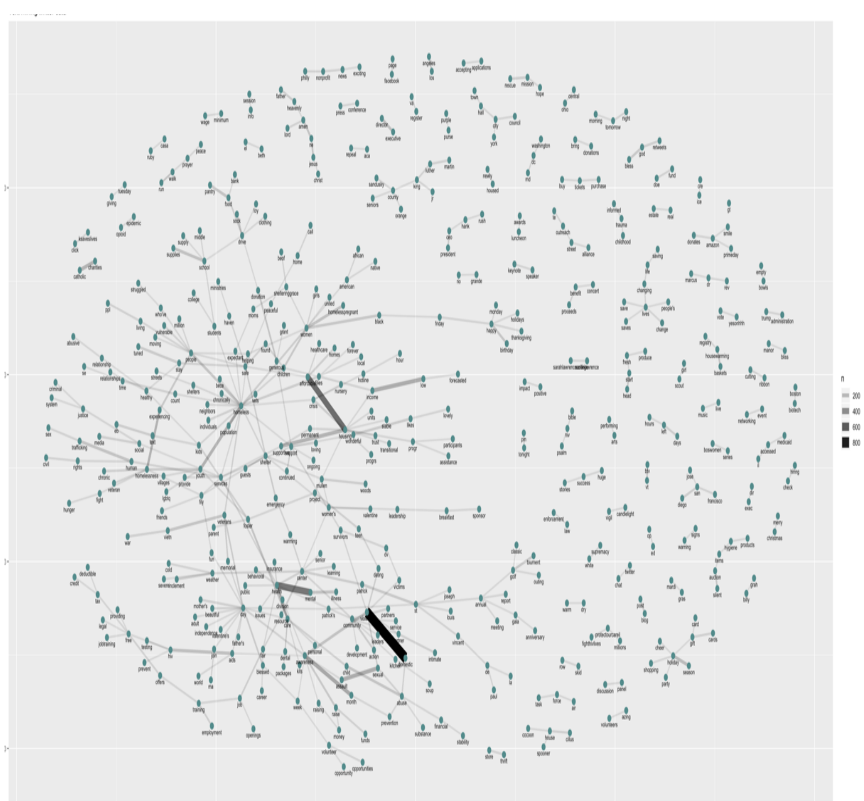
Table 4-9. Top 20 popular unigram (single word) and bi-grams (pairs of words)

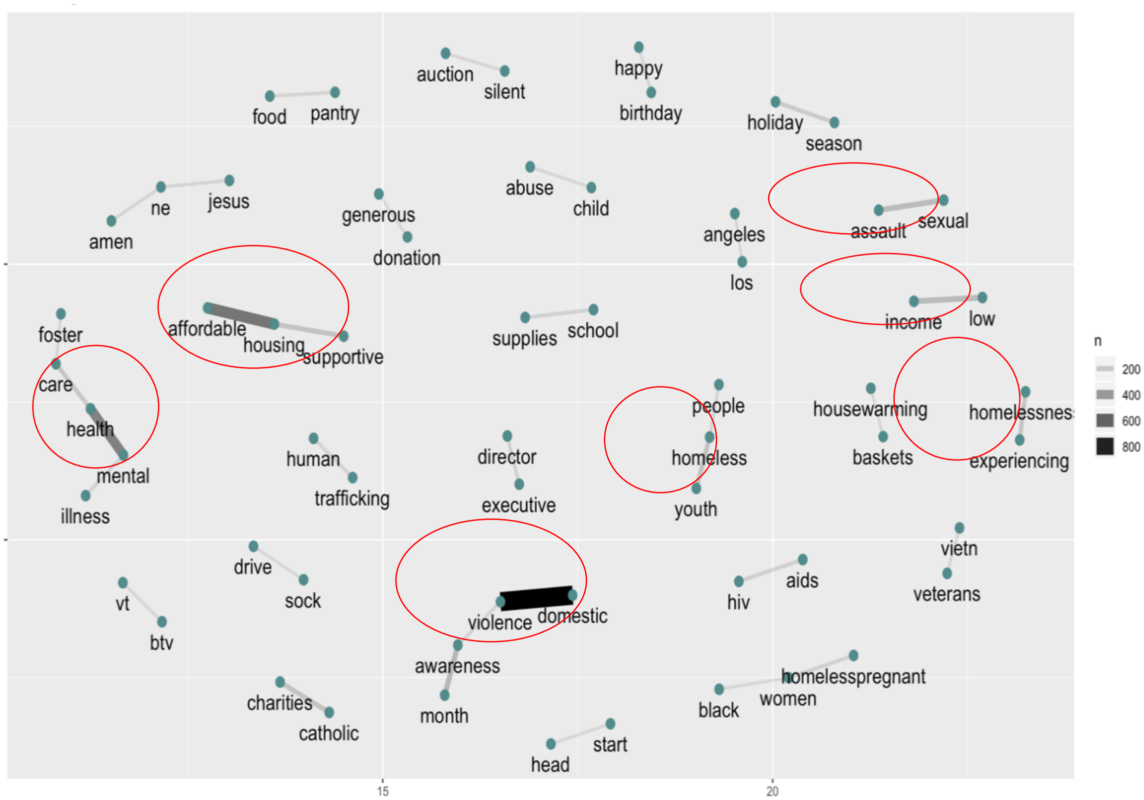
Unigram	Freq	Bi-grams	Freq
Support	3,962	Domestic Violence	896
Day	3,768	Affordable Housing	501
Join	3,456	Mental Health	473
Community	3,062	Awareness month	250
Women	2,902	Low income	234
Homeless	2,573	Sexual assault	226
Housing	2,531	Catholic charities	203
People	2,374	Homeless youth	195
Learn	1,958	Supportive housing	194
Homelessness	1,842	Women amp	182
Time	1,822	Health care	181
Center	1,745	Experiencing homelessness	165
Youth	1,739	Holiday season	156
Children	1,729	Executive director	142
Check	1,707	School supplies	131
Program	1,695	Mental illness	130
Week	1,643	Human trafficking	129
Families	1,639	Violence awareness	126
Health	1,602	Amp support	123

I visualized the network of co-occurred bi-grams as shown in Figure 4.10. There are some word-pairs significantly observed in the network with thicker lines, such as, domestic violence, affordable housing, mental health, sexual assault, homelessness experiencing, homeless youth, and low income.

The visualized network reveals that homelessness nonprofits frequently discuss problems and solutions about homelessness related issues. Specifically, they addressed problems such as homelessness experiencing, low-income, sexual assault, and domestic violence. Homelessness nonprofits also speak about solutions of those problems, such as affordable housing, school supplies, and food pantry.

Table 4-10. Word network of bi-grams





I then more closely scrutinized common topics extracted from the sample tweets by employing Unsupervised Machine Learning with LDA. 74,051 tweets were aggregated into 1,463 documents where each document represents Twitter messages sent by each organization. Based on the distribution of text data, the topic model assumes that each document consists of several latent topics, and each topic is characterized using a distribution over the linguistic units where the units with high frequency tend to co-occur.

Based on the results of bi-grams analysis and word network above, seven latent topics and terms in each topic were extracted. Table 4.11 shows the distribution of the seven latent topics and their 30 most relevant terms that are interpretable as themes in the collected document. The result of the LDA topic modeling reveals that the most popular topic produced by homelessness organizations and shared by others were Seeking support that comprises 29.8% of the corpus, indicating that organizations are often asking support on Tweet. Another finding from the founded topics is that organizations tend to focus on the target clients they serve. Three out of seven topics were the subgroups of the homeless; Women (13.4%), Homeless youth (14.7%), and Veterans (7.7%). The result of the content analysis on the organizational messages that had received attention provides insightful information on message-based advocacy strategies for nonprofit organizations in the homelessness field.

Table 4-11. Topics and their components of the tweets

	Theme	Keywords associated with topics	Distribution
1	Seeking support	Help, today, join, need, support, center, day, community, will, check, food, program, annual, great, get, volunteers, event, year, can, donate, learn, come, volunteer, families, now, new, house, tickers, make, looking	29.8%
2	Homeless Youth	Youth, support, help, community, kids, can, day, way, united, children, ymca, child, learn, families, school, summer, today, make, great, join, week, foster, new, homeless, get, give, shelteringgrace, free, see, moms	14.7%
3	Housing and Care service	Housing, health, people, via, will, affordable, can, new, work, hiv, care, affordablehousing, now, need, today, community, fight, communities, great, access, get, families, state, living, healthcare, city, take, check, make, learn	14.2%
4	Domestic Violence (Women)	Violence, women, domestic, abuse, survivors, victims, can, support, help, sexual, awareness, today, domesticviolence, dvam, join, ywca, call, day, girls, know, children, just, via, will, assault, one, hotline, child, safe, stand	13.4%
5	Emotional Dialogue	today, hope, life, mission, new, god, children, love, day, give, one, men, please, help, happy, lord, time, women, good, may, know, night, catholic, need, serve, last, every, charities	11.2%

6	Homelessness	Homeless, homelessness, people, housing, help, new, home, end, shelter, endhomelessness, need, join, will, women, drive, experiencing, please, amazing, socks, nonprofit, house, can, first, now, make, san, years, moving, warm, street	9%
7	Veterans	Veterans, day, today, honor, mental, health, Vietnam, wall, recovery, memorial, mentalhealth, veteran, addiction, btv, service, via, members, left, one, war, remember, served, lives, photos, names, photo, new, week, great, part	7.7%

4.3. Test of the Social Media Attention Model

In the previous chapter, I proposed nine hypotheses that explain the level of attention an organization receives on their social media messages. The explanatory model was tested with a series of regressions both at organizational and message levels. The results of the analyses help explain what kind of organizational characteristics and behaviors gets more audience attention, and what message strategy drives such attention.

4.3.1. Organizational-level Analysis

For an organizational-level analysis of Twitter use, the collected tweets and their characteristics were aggregated to the organizational/month level. Descriptive statistics including the mean, standard deviation, and range for each variable are reported in Table 4.12.

4.3.1.1. Measures

Public attention. Regarding the proxy indicators of public attention that an organizational message receives on Twitter, an organization had its Twitter messages retweeted on average 1,652 times per month, ranging from zero to 2,375,972. Favoriting an organizational tweet was less used by users than retweeting. The organizations in this study received on average 28.2 favorites on their tweets per month, ranging from zero to 6,637. Consistent with prior studies (e.g., Guo & Saxton, 2018; Barabasi & Albert, 1999), the two public attention factors reveal a heavily right skewed distribution – a power law distribution.

Network characteristics. By the same token, network characteristics, such as the number of followers, the number of public-list membership, and follower/following ratio were extremely right skewed and leptokurtic. Follower number is a popular indicator of network size of a Twitter user. At the time of data collection, the organizations had an average of 1,221 followers. On average, an organization was included 37.5 times in public lists of other users. Not surprisingly, *Follower/following ratio* of the average organization is 3.2, indicating that the number of followers of the organization is 3.2 times as much as the number of users the organization subscribes on Twitter. It is likely that some organizations use Twitter for broadcasting their own work rather than building a reciprocal relationship with stakeholders. All those three variables were spread out over a wide range: with a minimum of 1 to a maximum of 172,260 Twitter users who were following nonprofits, from zero to 3,191 users having the nonprofit organizations on their lists, and Follow/following ratio ranging from 0.09 to 1,769.

Volume of tweets (timing and placing). The 1,576 organizations in the sample of this study sent a total of 290,984 tweets during the constructed 12-month period. On average, each nonprofit organization sent out about 21.1 tweets per month, roughly 0.51 times per day. This volume is well below the 2.3 Tweets per day by Nonprofit Times 100 organizations (Lovejoy, Waters, & Saxton, 2012), or 4.4 tweets per day by 188 Civil Rights and Advocacy organizations (Guo & Saxton, 2018). Though the variation is spread out over a considerable range. Some organizations sent out multiple tweets every day, while the majority (89%) sent less than 1 tweet per day.

Targeting and connecting strategy. *Retweeting* is considered as the most popular communication tool on Twitter (Boyd et al., 2010). An organization can connect with specific constituents by addressing their previous tweets. I found that 20.32% of all tweets (n = 59,150) sent by the sample organizations were retweets. This is consistent with the 20.91% found by Guo and Saxton (2018) for 188 Civil Rights and Advocacy organizations, and more than 16.2% found by Lovejoy et al. (2012) for Nonprofit Times 100 organizations. The average organization retweeted about 4.3 times per month. Another Twitter's unique tool to connect with other users is *public reply messages* (direct messages) that allow organizations to target specific users by adding @username at the beginning of a tweet. In the sample, 5.8% of all tweets sent by the organizations were public reply, and an average organization sent 1.2 public reply in a month.

Other connection tools, such as hashtags, hyperlinks, and mentions, are not mutually exclusive and can be used in a tweet more than once. Hence, I used the frequency of these functions to measure the level of connection and targeting effort. *Hyperlinks* are one of the most frequently used connecting tools among the homelessness nonprofits in the current study. The average organization included 14.1 *URLs* in their monthly tweets. Only 14 organizations did not use hyperlinks at all, while the maximum number of URLs was 567. Regarding the use of *hashtags*, the average organization used 8.1 hashtags in their Twitter messages per month. I also found that the average organization mentioned other users (*User mentions)* 8.8 times per month.

Content richness Looking at the multimedia in tweets, the organizations included a *Photo or Video in their tweets.* On average, 3.6 tweets sent by an organization included a photo while only 0.2 tweets contained a video each month. The organizations also sent 0.3 tweets with a link to a photo per month. On average, 1.58 organizational tweets were related to homelessness issues out of 21.1 tweets per month.

Table 4-12. Descriptive statistics of all variables (n = 1,576 / 12 month)

Categories	Variables	Mean	Std. Dev.	Min	Max
Public attention	Retweets	2,267	48,341.2	0	2,375,972
	Favorites	28.2	160.8	0	6,637
Network size	Followers	1,221	5,573.2	1	172,260
	Public listed	37.5	76.9	0	3,191
Network influence	Follower/following ratio	3.2	32.1	0.09	1,769
Timing & pacing	# tweets	21.1	34.6	1	753
Targeting	Public reply	1.2	8.3	0	466
Connecting	Retweet others	4.3	12.7	0	378
	Hashtag	8.1	18.6	0	567
	URLs	14.1	22.7	0	551
	User mention	8.8	20.6	0	568
Content richness	tweets with ≥ 1 Photo	3.6	9.1	0	302
	tweets with ≥ 1 Video link	.2	1.4	0	86
	tweets with ≥ 1 Photo link	.3	1.7	0	50
	Homelessness related tweets	2.2	6.6	0	144
Sentiment and Tone	Positive tone	6.7	5.4	0	100
	Informal tone	0.5	1.7	0	80
Organization characteristics	Annual revenue (million)	12.8	44.0	0	2,228
	Employees number	232	589.7	0	16,766
	Years of operation	44.8	29.7	3	189

4.3.1.2. Model Test

In order to check multicollinearity source variables, Farrar-Glauber Test was conducted. The test reveals that the variance inflation factors for *tweets frequency* (VIF = 96.7), *word count* (VIF = 29.33), *emotional tone* (VIF = 33.84), and *tweets with urls* (VIF = 17.37) could be the root cause of multicollinearity. Pearson's zero-order correlation coefficient was used to closely examine association between pairs of variables. Table 4.13 shows the correlations for all explanatory variables, indicating some variables are highly correlated each other; *tweets frequency* and *tweets with urls* (r = .93), *emotional tone* and *word count (r=.94), tweet frequency* and *emotional tone (r=.90).* It is likely that adding urls in a tweet significantly increases the length of tweets (word count), and that organizations are likely to use positive terms when sharing their feelings on their tweets. After removing three variables, *tweets with urls, emotional tones,* and *word count,* the variance inflation factors for all predictors in the model are reduced less than 10. I then ran two Random Effects regressions on *number of favorites* and *retweets* respectively to estimate the effect of the predictors.

Table 4-13. Zero-Order Correlations for All Explanatory Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. Followers	1																			
2. Public listed	.72*	1																		
3. Follow ratio	.04*	.04*	1																	
4. TW frequency	.16*	.20*	-.02*	1																
5. Public reply	.07*	.07*	.00*	.51*	1															
6. Retweet others	.15*	.18*	-.01*	.72*	.29*	1														
7. Hashtags	.10*	.14*	-.01*	.80*	.48*	.65*	1													
8. URLs	.14*	.18*	-.01*	.93*	.38*	.55*	.67*	1												
9. Mentions	.18*	.21*	.01*	.81*	.60*	.85*	.73*	.63*	1											
10. Word count	.14*	.18*	.00*	.92*	.47*	.44*	.69*	.92*	.60*	1										
11. Photo links	.01	.00	.01*	.13*	.03*	.08*	.13*	.14*	.09*	.11	1									
12. Video links	.07*	.03*	.00	.20*	.13*	.14*	.13*	.21*	.19*	.16*	.02*	1								
13. Photos	.09*	.10*	-.02*	.71*	.32*	.45*	.60*	.62*	.54*	.64*	.08*	.10*	1							
14. Positive	.11*	.12*	-.01*	.77*	.67*	.40*	.65*	.66*	.69*	.75*	.12*	.12*	.64*	1						
15. Emotional	.13*	.16*	-.01*	.90*	.60*	.43*	.70*	.86*	.67*	.94*	.13*	.16*	.68*	.90	1					
16. Informal tone	.04*	.04*	-.01*	.52*	.62*	.21*	.49*	.50*	.39*	.57*	.04*	.12*	.38*	.50	.58*	1				
17. Homelessness	.05*	.06*	-.01*	.44*	.21*	.19*	.29*	.46*	.31*	.47*	.08*	.09*	.38*	.38	.47*	.24*	1			
18. Org age	.05*	.09*	-.01*	.11*	.02*	.07*	.08*	.10*	.09*	.11*	.00	.00	.08*	.07	.10*	.02*	-.04*	1		
19. Employee size	.12*	.16*	.00*	.07*	.03*	.04*	.05*	.06*	.07*	.07*	.00	.02*	.03*	.06	.08*	.02*	-.02*	.28*	1	
20. Total revenue	.13*	.15*	.00*	.03*	.03*	.03*	.03*	.03*	.04*	.03*	.00	.01	.01	.03*	.04*	.01	-.01	.17*	.85*	1

*p < .05

Table 4.14 presents the results of Random Effects Models on the *number of favorites* and *number of retweets*. All continuous variables except for *age* were transformed to natural log for their heavily skewed distribution.

In H1,2, and 3, I hypothesized the relationship between network characteristics (network size and network influence) and the level of attention to organizational tweets. Among three indicators of Network characteristics, the number of followers were positively associated with both measures of attention. The result also indicates a negative and significant association between follower/following ratio and number of retweets, but this association is not significant with favorite. Therefore, H1 is supported with both measures, while H2 is not supported and H3 is partly supported with number of retweets.

H4 proposed that the number of tweets sent by an organization would be positively associated with the level of attention the organization receive on Twitter. The result of the regression analyses indicates that there is a significant and positive relationship between the volume of organizational tweets and the level of attention. Therefore, H4 is supported.

H5 predicted that the number of public reply messages sent by an organization would be positively associated with the level of attention. The result of the regression analyses on this relationship show a significant, but different directions between the number of favorites and number of retweets. The number of favorites is positively associated with the number of public-reply, whereas there is a negative relationship between the number of retweets and the number of public-reply. This mixed result is consistent with the work by Guo and Saxton (2018). Thus, H5 is partially supported.

H6 examined the effect of connecting strategy. In H6b, I proposed that the number of hashtags in organizational tweet messages would be positively associated with the level of attention. The result of regression analyses reveals that there is significant and positive relationship between the volume of hashtags and the two attention measures. Thus, H6b is supported. H6c predicted that the number of mentions used in organizational tweets would be positively associated with the level of attention. The result reveals a significant and positive relationship between the number of mentions and the both attention measures. Therefore, the H6c is supported. H6d hypothesized a positive relationship between the number of retweets that an organization reposted others' tweets and the level of attention the organization would receive. The regression result reveals that the level of attention is significantly associated with the number of retweets, but the direction of the relationship differs between the two dependent variables. To be specific, the number of retweets of an organization's tweets by others is positively associated with the number of retweets that the organization repost others' tweets; by contrast, the number of favorites on an organization's tweets is negatively associated with the number of retweets that the organization repost others' tweets. This is also consistent with the previous work by Guo and Saxton (2018). H6c is partially supported.

Next, in H7 and 8, I examined content richness strategy. H7a, H7b, and H7c proposed that visual content in tweets would have a positive relationship with the level of attention. The results of the regressions reveal that only tweets with photo (H7a) is positively associated with the level of attention (the number of retweets and favorites). However, including photo (H7b) or video link (H7c) in tweets fails to achieve significant association with the dependent variables. Therefore, only H7a is supported. H8 predicted that homeless related tweets are more likely to receive attention. The result reveals that there is significant and positive relationship between homelessness related content and the level of attention. Thus, H8 is supported.

Finally, H9 and H10 examined sentiment and tone strategy. H9 hypothesized a positive relationship between the level of attention and positive tone. H10 proposed that there would be a positive relationship between the level of attention and informal tone. Both variables are significantly and positively associated with the two attention measures, supporting H9 and H10.

Table 4-14. Determinants of Public Attention to Tweets: Organizational Level

Variables	Favorites		Retweets	
	B	*SE*	*B*	*SE*
Network Characteristics				
Followers (H1)	.475***	.030	.335***	.034
Public listed (H2)	-.009	.014	.002	.046
Follower/following ratio (H3)	-.009	.029	-.084*	.033
Communication Strategy				
# tweets (H4)	.336***	.010	.417***	.010
Public reply (H5)	.036***	.007	-.030***	.007
Hashtag (H6b)	.086***	.006	.083***	.007
User mention (H6c)	.134***	.008	.168***	.008
Retweet others (H6d)	-.067***	.007	.408***	.008
Content Strategy				
# tweets with ≥ 1 Photo (H7a)	.085***	.006	.067***	.006
# tweets with ≥ 1 Photo link (H7b)	.009	.010	-.046***	.010
# tweets with ≥ 1 Video link (H7c)	-.006	.009	-.007	.009
Homelessness related tweets (H8)	.062***	.005	.041***	.006
Positive tone (H9)	.244***	.007	.019**	.007
Informal tone (H10)	.045***	.005	.025***	.005
Control variables				
Organizational age	.002	.001	.002*	.001
Employee size	.011	.013	.026	.015
Total revenue	.004	.021	-.027	.024
n	1,572		1,572	
T	12		12	
N	18,864		18,864	
F statistic (*df*)	2625.93(17)***		2885.78(17)***	
Adjusted R^2	.70		.72	

*** p < .001, ** p < .01, * < .05

4.3.2. Message-level Analysis

4.3.2.1. Descriptive statistics

Table 4.15 presents descriptive statistics of all variable of the 8,000 message sample drawn by disproportionate stratified sampling.

Public attention. On average, an organizational tweet received 1.16 favorites (*SD* = 3.13) and were retweeted 0.57 times (*SD* = 1.78) by other users.

Network characteristics. On average, organizations had 1,186 (*SD* = 4,895.4) followers and 38.32 (*SD* = 107.42) public listed on Twitter. *Follower/following ratio* of the average organization is 4.69 (*SD* = 61.45), indicating that the number of followers of the organization is 3.2 times as much as the number of users the organization subscribes on Twitter.

Communication strategy. Among the 8000 organizational tweets, only 6% messages were reply messages to other users, while connecting strategy were frequently used; over three-quarters (76.6%) of the tweets contained at least one urls, nearly one-third with hashtags (32.8%), and 25.1% with user mentions.

Content strategy. Photo were more used with photo (17.3%) and phone link (2.4%), whereas video was barely used in the organizational tweets (0.3%). Slightly over 12% of the tweets contained at least one homelessness related word. The average positive tone rated 6.7 (*SD* = 9.4) on a scale 0 to 100, and informal tone was rated 59.4 (*SD* = 3.25).

Organizational characteristics. The average revenue of the 1,551 organizations in the sample was $1.2 million (*SD* = $39.5 million), having 229.7 paid employees (*SD* = 583.3). The average age of the organizations was 45.7 years (*SD*= 28.5).

Table 4-15. Descriptive statistics of all variables (n = 8,000)

Variables	Unit level	N(%) Mean (SD)	Min	Max
Public attention				
Retweets	Message	.57 (1.78)	0	55
Favorites	Message	1.16 (3.13)	0	147
Network characteristics				
Network size				
Followers	Organization	1,186 (4,895.40)	1	172,260
Public listed	Organization	38.32 (107.42)	0	3,191
Network influence				
Follower/following ratio	Organization	4.69 (61.45)	.09	1,769
Communication strategy				
Targeting				
Public reply	Message	477 (6.0%)	0	1
Connecting				
Hashtag	Message	2,624 (32.8%)	0	1
URLs	Message	6,125 (76.6%)	0	1
User mention	Message	2011 (25.1%)	0	1
Content strategy				
Richness of content				
tweets with Photo	Message	1387 (17.3%)	0	1
tweets with Video link	Message	30 (0.3%)	0	1
tweets with Photo link	Message	188 (2.4%)	0	1
Homelessness related tweets	Message	974 (12.2%)	0	1
Sentiment and tone				
Positive tone	Message	6.7 (9.43)	0	100
Informal tone	Message	59.4 (3.25)	0	100
Organization characteristics				
Annual revenue (million)	Organization	1.2 (39.5)	0	1,091
# Employees	Organization	229.7 (583.3)	0	7,.668
Years of operation	Organization	45.7 (28.5)	4	189

4.3.2.2. Model Test

Table 4.16 presents the results of both Multilevel Poisson models and General Linear Mixed (GLM) negative binomial models on number of retweets and number of favorites, using the R function glmer() and glmer.nb() respectively. The Akaike Information Criterion (AIC) for the GLM negative binomial models are 20,450.4 for favorite and 13,845.6 for retweets, which are lower than the AIC for the Multilevel Poisson models (22483.4 and 14910.2), signifying that the GLM negative binomial models are more robust. I also ran mixed effects logistic regression models with binary outcome variables, the results of which are consistent with the multilevel poisson and GLM negarive binomial models as seen in Table 4.17.

Number of tweets (H4) and Retweeting Others (H6b) were not included in the regression models because the two variables are not measurable at message level. Another two variables (Tweets with photo link and video link) were dropped due to low variance. None of the Variance Inflation Factors (VIF) among the independent variables exceeded 4.0, which is an indication that the variables were independent and thus appropriate for inclusion in a regression model (Allison, 1999).

Network size were positively associated with the both attention measure, supporting H1, while the other two measures of network characteristics were not significant. Holding other variables constant, public reply messages were less likely to receive audience attention than normal tweets. Thus, H5 is rejected.

The three connecting strategy variables reveal mixed results. Tweets with Hashtags (H6b) and Tweets with Mentions (H6c) were positively associated with favorites and retweets. However, Tweets with URls were negatively significant only with favorites. Thus, H6a is rejected.

As for content strategy, photo included tweets than tweets without photo were more likely to receive attention. Thus, H7a is supported. Homelessness related messages were also positively associated with favorites and retweets, supporting H8.

Positive tone was significantly and positively associated with favorite, partially supporting H9, while informal tone fails to achieve significance in any of the two models.

Table 4-16. Determinants of Public Attention to Tweets: Message Level

	Multilevel Poisson Regression		GLM negative binomial regression	
	Favorites	Retweets	Favorites	Retweets
Variables	*B*	*B*	*B*	*B*
Network Characteristics				
Log (followers) (H1)	.398***	.452***	.399***	.454***
Log (public listed) (H2)	-.009	-.029	-.011	-.031
Follower/following ratio (H3)	.000	.000	.000	.001
Communication Strategy				
# tweets (H4)	-	-	-	-
Public reply (H5)	-1.051***	-.960***	-.925***	-.915***
URLs (H6a)	-.240***	.026	-.194***	.009
Hashtag (H6b)	.160***	.187***	.181***	.180***
User mention (H6c)	.492***	.340***	.543***	.475***
Retweet others (H6d)	-	-	-	-
Content Strategy				
# tweets with ≥ 1 Photo (H7a)	.232**	.313***	.195***	.276***
# tweets with ≥ 1 Photo link (H7b)	-	-	-	-
# tweets with ≥ 1 Video link (H7c)	-	-	-	-
Homelessness related tweets (H8)	.202***	.325***	.198**	.319***
Positive tone (H9)	.010***	-.001	.009***	-.005*
Informal tone (H10)	-.009*	-.005	.001	-.001
Control variables				
Organizational age	.000	.001	.001	.001
Log (employee size)	.002	.002	.001	.001
Log (revenue(million))	.030	.030	.031	.028
n	7,688		7,688	
AIC	22483.4	14910.2	20450.4	13845.6

*** p< .000 ** p<.001 * p<.01

Table 4-17 Results of Mixed Effects Logistic Regressions

	Mixed effects logistic regression	
	Favorites	Retweets
Variables	*B*	*B*
Network Characteristics		
Followers (H1)	.481***	.497***
Public listed (H2)	-.001	-.020
Follower/following ratio (H3)	.002	.002*
Communication Strategy		
# tweets (H4)	-	-
Public reply (H5)	-1.118***	-1.26***
URLs (H6a)	-.397***	-.041
Hashtag (H6b)	.313***	.255***
User mention (H6c)	.713***	.561***
Retweet others (H6d)	-	-
Content Strategy		
# tweets with ≥ 1 Photo (H7a)	.226*	.362***
# tweets with ≥ 1 Photo link (H7b)	-	-
# tweets with ≥ 1 Video link (H7c)	-	-
Homelessness related tweets (H8)	.296**	.385***
Positive tone (H9)	.019***	-.006
Informal tone (H10)	-.001	-.000
Control variables		
Organizational age	.001	.001
Employee size	-.006	.014
Total revenue(million)	.076*	.050
n	Obs: 7,688 Group: 1,491	
AIC	9327.2	8332

*** p< .000 ** p<.001 * p<.01

4.4. Summary

In this chapter, I presented the findings from statistical analyses on 4,615 homelessness organizations and their 326,620 tweets sent between September 1st 2016 and August 31st 2017.

In phase one, I explored the characteristics of nonprofit organizations in the homelessness sector and their social media use pattern. As I attempted to identify and build a data set of nonprofit organizations in the homeless field across nation, the descriptive analyses have provided a national picture of the homelessness field of the nonprofit sector in the United States.

In Phase two, I utilized unsupervised machine learning with LDA topic modeling approach to identify popular topics produced by homelessness nonprofit organizations and shared by other users on Twitter. The results reveal that the most popular topic is seeking support and call to action related words. The organizations also often talked about subgroup of homeless population who they advocate for, such as 'Homeless Youth', 'Women', and 'Veterans'.

In Phase three, Random Effects Regressions at organizational level and Negative Binomial regressions at message level have been conducted to test the hypotheses presented in Chapter Three. Table 4.18 presents the summary of the model testing. The results revealed that, when it comes to homelessness sector, effective strategies and tactics can strengthen social media-based nonprofit advocacy.

In next chapter, I will summarize main findings, discuss limitations, and cover the theoretical and practical implications of the current study.

Table 4-18. Summary of model testing

Variables	Organizational level *Favorite*	Organizational level *Retweets*	Message level *Favorites*	Message level *Retweets*
Network Characteristics				
Followers (H1)	(+)***	(+)***	(+)***	(+)***
Public listed (H2)			(+)***	(+)***
Follower/following ratio (H3)		(-)*	(+)*	(+)**
Communication Strategy				
# tweets (H4)	(+)***	(+)***		
Public reply (H5)	(+)***	(-)***	(-)***	(-)***
URLs (H6a)			(-)***	
Hashtag (H6b)	(+)***	(+)***	(+)***	(+)***
User mention (H6c)	(+)***	(+)***	(+)***	(+)***
Retweet others (H6d)	(-)***	(+)***		
Content Strategy				
# tweets with ≥ 1 Photo (H7a)	(+)***	(+)***	(+)**	(+)***
# tweets with ≥ 1 Photo link (H7b)		(-)***		
# tweets with ≥ 1 Video link (H7c)				
Homelessness related tweets (H8)	(+)***	(+)***	(+)***	(+)***
Positive tone (H9)	(+)***	(+)**	(+)***	
Informal tone (H10)	(+)***	(+)***		
Control variables				
Organizational age		(+)*	(+)***	(+)**
Employee size				
Total revenue(million)			(+)*	(+)*

Chapter 5. Discussion

This dissertation attempts to fill a critical void in the existing literature on the effectiveness of social media-based nonprofit advocacy. Specifically, the study aims to develop a theoretical model to test the determinants of public attention obtained by advocacy organizations both at the organizational and message levels.

Extending Guo and Saxton's Social Media Advocacy model, I propose a comprehensive model containing three major categories that explain the level of public attention. The first category is network characteristics, which includes network size and network influence. The second category is communication strategy, which contains three subcomponents of timing and pacing, targeting, and connecting strategy. The third category is content strategy with its two elements of content richness and sentiment/tone.

Nationwide data on homelessness nonprofits in the U.S. were compiled by combining multiple data sources; 326,620 Twitter messages sent by the sample organizations were collected via the Twitter API. Data analysis consisted of three phases.

The findings from phase one present the national description of nonprofit organizations in the homelessness sector and their social media adoption and use. In phase two, a series of content analyses was conducted on the Twitter messages sent by homelessness nonprofits to explore topics discussed by the organizations. The findings from the topic modeling via LDA identified seven themes that were most frequently employed by homelessness nonprofits while successfully obtaining attention from other users. The seven themes included seeking support, homeless youth, housing and care service, domestic violence, emotional dialogue, homelessness, and veterans.

In the third phase, the study's hypotheses were tested both at the organizational and message levels. The analysis generated the following major findings: network size, connecting strategies, informative content, and positive tone are found to be important determinants of the attention on social media both at the organizational level and message level. There may be different attention mechanisms between the organizational level and message level as some factors (e.g., public reply) are found to have a significant but different direction of relationship with attention between the two levels.

In this chapter, I will discuss the findings from the analyses of the three phases, as well as present the contributions of this study to the existing literature and nonprofit advocacy practice. I will also address limitation of the study and directions for future research.

5.1. Discussion of the Findings

This study is the first to provide a nationwide profile of nonprofit organizations in the homelessness sector. The first phases of the analysis on 4,615 organizations present the characteristics of homelessness organizations in the US. The number of nonprofit organizations in the homelessness sector has been rapidly growing since the 1960s. As of 2014, the total revenue of the nonprofit homelessness sector was slightly over $44 billion, and most of the revenue was spent in program services. This finding indicates that the nonprofit sector annually spent over $40 billion to serve the homeless.

The analysis of social media adoption and use by homelessness nonprofits revealed that over 60% of the organizations had at least one social media account, indicating that social media has become a popular communication channel and advocacy tool for homelessness nonprofits. The two most popular platforms were Facebook and Twitter, which is consistent with previous studies (Lovejoy & Saxton, 2012; Asorwoe, 2017). The bivariate analysis found a positive relationship between organizational resource capacity and Twitter adoption, revealing that larger and older organizations are more likely to have Twitter handles, which is consistent with the previous studies on the adoption of IT technology of organizations (Corder, 2001; Gormley & Cymrot, 2006; J. G. McNutt & Boland, 1999; Schneider, 2003; Zorn et al., 2011). Despite the lower financial barriers to adoption, small organizations appear to find it difficult to have a presence on Twitter. Interestingly but not surprisingly, homelessness organizations are more likely to send tweets during working days and hours, which is similar to the time pattern of the overall tweets sent in the US (see Lee, 2016).

In phase two, I conducted a topic modeling analysis on organizational tweets that were retweeted by other users at least once to identify themes that obtained attention. Two out of the seven themes extracted from the topic modeling analysis were communicative themes: seeking support and emotional dialogue. For instance, the topic of seeking support appeared often with call-to-action words, such as help, join, need, support, and specific agenda of support, such as event, donate, and volunteers. The theme of the emotional dialogue was often sent with sentimental terms, such as love, hope, happy, and please. This result reveals a trend on Twitter that people tend to pay more attention to a positive and sentimental message than negative framed messages.

The rest of the themes extracted from the topic modeling were subgroups of the homeless population, such as women (domestic violence), homeless youth, and veterans, or homelessness-related issues such as housing and care services. This result indirectly supports hypothesis 8. To be specific, organizational tweets that are related to specific homelessness groups, issues, or services often get retweeted by other users.

The combined findings from the model testing at organizational and message levels help bring some interesting light into the study of the determinants that influence public attention to nonprofit advocacy messages on social media. Overall, the combined findings suggest that network characteristics (number of followers), connecting strategy (hashtags and user mentions), and richness of content (photo, homeless related tweets) are significant factors that explain public attention to both organizations and individual messages.

This study developed a single model and applied it to both organizational and message level analyses. The contradictory findings between organizational level and message level tests suggest that there are different attention mechanisms between the two. For instance, the number for public-reply was found to be positively related to the number of favorites at the organizational level, while public reply messages were less likely to receive favorites than other organizational tweets at the message level analysis. At the organizational level, frequent employment of public reply may indicate that the organization actively communicates with other users; this encourages public message recipients and other users to pay more attention to the organization's future tweets, leading to the increase in the aggregated amount of attention that the organization's tweets receive. At the message level, on the contrary, a public-replay message is targeted at a specific user, and other people are less likely to pay attention to such a message because it is not relevant to them. Thus, the findings suggest that targeting strategy (public-reply) may be effective in the long term but is not useful when an organization aims to capture public attention on a specific message.

Consistent with prior research (Guo & Saxton, 2018), the two attention measures show inverse relationships with the number of retweets of others. The number of tweeting others is significantly related to both but is found to be negatively associated with the number of favorites while positively related to the number of retweets. Guo and Saxton (2018) interpreted that "Retweeting as a function is often used as a reciprocal act of giving and receiving attention . . . favoriting is often used as a bookmarking tool where a user keeps useful tweets for future reference" (p.21). A user is less likely to favorite an organizational tweet that is simply a retweet of others, while the user is reciprocally retweeting back to the organization.

Moreover, the findings from the variables in the content strategies highlight the importance of visual and textual content in determining the extent to which an organization's message captures the audience attention. First, while photo or video links are found to be insignificant factors in obtaining user attention, the use of photos in an organization's tweets is positively related to the attention at both the organizational and message levels. On Twitter, photo or video links require that users take a further action (clicking) to see the visual content, while a photo in a tweet is directly shown on the users' Twitter feeds. The results suggest that a user is more likely to favorite or retweet a tweet that directly shows visual content, rather than a tweet containing information that demands further action to be seen.

Second, informative content, positive framing, and informal tone are found to be significant determinants in capturing users attention. These results suggest that when it comes to the social media setting where the core attribute is textual content, "what to speak" and "how to speak" likely matter to garner the attention of others. Specifically, the number of homelessness related messages in an organization's tweets is significantly and positively related to the level of attention the organization acquires. An individual message that addresses a specific homelessness issue is more likely to be favorited and retweeted than other messages (i.e., tweets not related to homelessness issues). Positive framing is also found to be an effective strategy both at the organizational level and message level. However, due to the qualitative difference between favorites and retweets, users are not likely to retweet a positive message, while they are more likely to express their positive emotion (i.e., favorite) to the tweet. These combined findings indicate that informal tone in a message does not attract attention, although it works at the organizational level.

5.2. Theoretical Contributions

This study makes a significant contribution to the current literature on social media-based nonprofit advocacy by developing an explanatory model that explains the determinants of public attention obtained by advocacy organizations. Building on Guo and Saxton's model, the study further develops the theoretical model by adding more factors and testing it both at the organizational level and message level. More specifically, this study adds to the literature on message strategies for nonprofit advocacy in social media settings. Advocacy scholars have highlighted the importance of message strategy in obtaining support for advocacy issues (Scudder & Mills, 2009; Weberling, 2012). Given that social media form a message system, this study has investigated the diverse aspects of textual and visual content on social media to build a solid foundation for the content strategy -- what should be said and how to frame a message (e.g., visual content, informative message, positive framing, and informal tone).

Second, the study contributes new knowledge to methodological discussions on studying homelessness nonprofits. This is the first study that attempts to capture the national picture of homelessness nonprofits in the U.S. Prior studies on nonprofit subsectors have used NTEE codes that impose several critical limitations. In the case of homelessness sector, organizations serving homeless persons are often categorized as 'human services' (P), 'mental health & crisis intervention' (F), religion-related (X), or others. A study analyzing housing and shelter nonprofits in Washington found that only 20 percent of homeless housing providers were actually coded as "Housing & Shelter" (L) by the NTEE system (Fyall et al., 2018). I introduced a new method for detecting homelessness organizations that addresses the shortcomings. Using a national database of homeless shelter beds as well as a list of attendees for a national conference on homelessness advocacy, I identified 4,615 nonprofit organizations across the nation by matching them with 990 Forms. With the newly developed data, the dissertation, for the first time, provides a national description of the history and geographic distribution of homelessness nonprofits and their financial and human capacity in serving the homeless.

Furthermore, this study is one of the first to examine social media use among homelessness nonprofits. Given the increasing use of social media among homeless individuals (Yost, 2012) and the rise in online advocacy campaigns on homeless issues (Creedon, 2014), social media have considerable potential as an advocacy and communication tool for nonprofit organizations in this field. The results of this study provide us with a wealth of knowledge about how organizations working on homeless issues are being to integrate social media into their advocacy efforts.

Third, I employed Big Data and computational methodology to better understand a large amount of social media messages sent by nonprofit organizations. As most previous studies have been limited by small sample size and manual coding in identifying topics in social media messages, my study employed an unsupervised machine learning approach to automatically identify topics in a large amount of data on Twitter. The empirical approach employed in this study can be applied to other nonprofit subsectors to identify patterns of online discussion on social problems and policy issues.

5.3. Implications for Nonprofit Advocacy on Social Media

The study also has some practical implications for nonprofit practitioners and advocates. Overall, the findings suggest that nonprofit organizations should spur efforts to increase their network size on social media, speak frequently, connect with others (e.g., hashtags and mentions on Twitter), contain informative and image content, and speak positively with an informal tone. They should also understand that there are different strategies based on the purpose of the tweets. For instance, public-reply messages targeted at a specific user may encourage users to pay more attention to what the organization says, but may not be effective when the organization wants to diffuse a specific message. Likewise, retweeting others' messages can build a reciprocal tie with others, but the sharing function does not affect the emotional interest (favorite) of users.

Next, for social media content generators in organizations, it is critical to understand how to write a valid message within the Twitter’s character count limit of 280. The findings of the study suggest that an organization should send an informative message that contains information that users expect to obtain from the organization (e.g., homelessness related topics in the case of this study). A positive and informal tone on social media may be an effective strategy to attract more attention.

The findings from the analysis also suggest that although organizational capacity, such as financial and human resources, may affect their social media usage, how much attention an organization acquires on social media depends less on the organization's resources and more on effective use of social media. That is, no matter how small, an organization can increase awareness and drive audience attention by using social media strategically.

5.4. Limitations of the Study

Several important limitations of this study should be noted. The first lies in the assumption that the Twitter messages of homelessness nonprofits are produced for advocacy purpose. As mentioned in Chapter Two, although human service organizations -- especially those that serve vulnerable populations such as the homeless -- often use social media for advocacy efforts, there are other types of messages besides advocacy, such as those about fundraising, volunteer seeking or service programs. Failure to exclude messages not intended for advocacy could create problems for a typology of social media-based nonprofits as adopted in this study. Nevertheless, in their use of social media primarily for advocacy, nonprofit organizations that serve the homeless population apparently differ from other nonprofit subsectors such as education, art, and religion.

Second, although this study collected twelvemonths worth of panel data, the analyses reported here are limited in mostly being cross sectional. A study based on trajectories of audience attention would yield more specific results than founded here. For instance, it is important to know whether attention to an organization's messages persists or increases over time. Such an approach was beyond the scope of this study and should be considered for future research.

Third, the current study only focusses on Twitter among many other social media platforms, which may have produced bias results. For example, Facebook is the most used social media platform for homelessness nonprofits (60.3%). Furthermore, it seems that Facebook might be more useful than Twitter to reach out to a larger audience. A Pew Research Center survey (2018) finds that, as of 2018, Facebook is the most dominant social media platform used by U.S. adults (68%), while only a quarter of Americans are Twitter users. Thus, although Twitter was the second popular social media channel among the homelessness nonprofit organizations, the results of this study can be valid only with Twitter; caution must be exercised to generalize the findings to other social media channels.

Fourth, although public attention is a critical outcome that indicates the effectiveness of social media efforts, one important question remains -- whether these lead to further outcomes as proposed in the study's conceptual model (see Figure 2.1). The study did not analyze this. Indeed, there has been a debate whether advocacy efforts via social media sites enable nonprofit organizations to strengthen traditional offline advocacy. Proponents believe that nonprofit advocacy on social media creates new opportunities to access information, cooperate, and participate in advocacy activities (Deschamps & Mcnutt, 2014). Opponents, on the other hand, argue that social media advocacy may be promoting a form of "slacktivism," a false sense that online participation alone will produce definitive social change (Brady et al., 2015; Dave Karpf, 2009). With the false belief, advocacy efforts on social media may demotivate potential supporters, and in turn, reduce commitment and participation in offline advocacy activities. In short, the jury is still out whether the outcome of advocacy efforts within social media lead to further offline outcomes. Therefore, future research should conduct more qualitative and quantitative studies that cover further tangible and intangible outcomes of social media-based nonprofit advocacy. In order to better understand the outcomes of nonprofit advocacy on social media, future research may examine how online and offline advocacy efforts interactively affect the goals of advocacy organizations.

Chapter 6. Concluding Remarks

This dissertation examined the effectiveness of nonprofit advocacy on social media. With nationwide data on homelessness nonprofits in the United States, this is the first to examine how the such organizations use social media, what they frequently say on social media, and how effectively they use social media in order to garner public attention.

This study makes significant contributions to the literature and practice. The first contribution is further development of the Social Media Advocacy Model by Guo and Saxton (2018). The proposed model contains four categories that affect the level of public attention. The first category is network characteristics along with two elements of network size and network influence. The second category is the communication strategy that contains three subcomponents of timing and pacing, targeting, and connecting strategy. The third category is the content strategy with its two elements of content richness and sentiment/tone.

This dissertation also provides practical insights for nonprofit practitioners and advocates. In order to capture public attention, nonprofit organizations should spur efforts to increase their network size on social media, speak frequently, connect with others (e.g., hashtags and mentions on Twitter), contain informative and image content, and speak positively with an informal tone. They should also understand that there are different strategies for use of Twitter, based on the purpose of the tweets. For instance, public-reply messages targeted at a specific user may encourage users to pay more attention to what the organization says; however, it may not be useful when the organization wants to diffuse a specific message. Likewise, retweeting others' messages can build a reciprocal tie with others, but the sharing function does not affect the emotional interest (favorite) of users. Another important insight for nonprofit organizations is that how much attention an organization acquires on social media depends less on the organization’s resources, but more on effective use of social media. That is, no matter how small, an organization can increase awareness and drive audience attention by using social media strategically.

Future research is needed to address further tangible and intangible outcomes of social media-based nonprofit advocacy, and interaction between online and offline advocacy efforts and their influence on the ultimate goals of nonprofit advocacy.

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