TWEET YOUR #MO AND SAVE A BRO

Micro-mobilization dynamics and outcomes
of online social movement campaigns

Anna Priante

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TWEET YOUR #MO AND SAVE A BRO
MICRO-MOBILIZATION DYNAMICS AND
OUTCOME OF ONLINE SOCIAL MOVEMENT
CAMPAIGNS

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To my parents and sister.

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Chapter 1

Introduction

1.1 Preface

Since 2003, November has been the month of the moustache. Men shave theirs off on 1 November and, by the end of month, thousands of pictures of fancy work-in-progress moustaches are posted on social media. The goal is to raise awareness of prostate and testicular cancer, to promote conversations about prevention and early detection behavior, and to raise funds for cancer research and men's health programs. The Movember campaign started in 2003 and came from an idea by two Australian friends. Since then, with more than 5 million people participating, 55 million dollars raised, and 1,200 projects funded (Movember, 2017), Movember has become the biggest movement for men's health worldwide.

In the summer of 2014, more than 17 million people were filmed having a bucket of water and ice dumped on their heads. Millions of videos were posted on Twitter, Facebook, and Instagram. The goal was to raise awareness for amyotrophic lateral sclerosis (ALS): Accept the Ice Bucket Challenge, show it to the world, and make a donation to the Amyotrophic Lateral Sclerosis Association. Launched by an American student diagnosed with ALS, the Ice Bucket Challenge campaign went viral, also thanks to the participation of many celebrities. More than 115 million US dollars was raised and used to fund ALS research (Trejos, 2017; Woolf, 2016). Several other examples of advocacy campaigns heavily relying on social media come to mind, such as the breast cancer awareness month promoted by the Pink Ribbon organization or the SunSmart media campaigns to prevent skin cancer.¹

Social movement organizations (SMOs) widely use social media to organize collective action for social change (Earl, Hunt, & Garrett, 2014; Earl & Kimport, 2011; Hara & Huang, 2011; Lovejoy & Saxton, 2012; Murthy, 2018; Van Laer & Van Aelst, 2010), such as health awareness campaigns (Chou, Prestin, Lyons, & Wen, 2013; Koskan et al., 2014; Maher et al., 2014; Thackeray, Neiger, Burton, & Thackeray, 2013; Ventola, 2014; Wehner et al., 2014). Social change can be achieved by promoting online conversations of impact and by inspiring people to move from their armchair to the street. However, very few studies have assessed the effectiveness of online social movement campaigns to generate meaningful social change. While some of these new forms of activism, such as online campaigns and petitions, are quite successful, as the examples above show, online activism is often accused of producing weak and lazy forms of collective action, also known as “slacktivism” (Morozov, 2009), that require little effort to participate and rarely foster actual change or translate into concrete, meaningful (offline) action (Gladwell, 2010;

¹ For more information, see the Pink Ribbon International (<http://pinkribbon.org/about/>) and SunSmart programs (<http://www.sunsmart.com.au/about>).

Kristofferson, White, & Peloza, 2014; Lewis, Gray, & Meierhenrich, 2014; Morozov, 2009). In light of these critical views, I argue that when campaigns using social media means are effective, they can be an important instrument for SMOs and health and nonprofit organizations to reach their desired goals.² Social media facilitate direct people's engagement and participation in collective action by providing fast, low-cost ways to organize, mobilize, and communicate directly during campaigns (Bennett & Segerberg, 2013, 2015). In other words, individual agency is important in the organization and outcomes of collective action by online means, and the success of SMOs and their campaigns might depend on the extent to which individuals and groups mobilize to support them (Bimber, Flanagin, & Stohl, 2012; Della Porta & Diani, 2006; Tindall, 2004). Therefore, I argue that focusing on individual-level mobilization can shed light on how effective social movement campaigns using social media are at achieving social change.

This dissertation examines the micro-mobilization dynamics at play that can explain the effectiveness of online social movement campaigns as collective events organized by SMOs via social media when their goal is social change. The scope of this dissertation includes micro-dynamics of mobilization, which I define as micro-structural and social-psychological dimensions, such as social networks, identity, framing, and emotions, and related processes that are relevant to individual mobilization (Della Porta & Diani, 2015; Elliott & Earl, 2018; Snow, Soule, & Kriesi, 2004). Consequently, the level of analysis is the individual, and the focus is on individual-level mobilization dynamics and related outcomes during online social movement campaigns. The central research question of this dissertation is:

How and why do micro-mobilization dynamics explain the effectiveness of online social movement campaigns in achieving social change?

This dissertation comprises six chapters seeking answers to this question and presents research based on a multidisciplinary, mixed-method approach combining theories and methods from sociology, social psychology, communication science, and computational social science.

This introduction provides a brief overview of the state of the art in research on social movements, collective action, and social media (Sections 1.2), leading to the formulation of the research problem and the main research question of this dissertation (Section 1.3). Then, I present an outline of the research sub-questions and related chapters (Section 1.4), the peculiarities of the data used (Section 1.5), a reflection on the overall scientific

² On the whole, this dissertation presents its findings through a first-person perspective. From time to time, however, the pronoun "we" is used to emphasize the collaborative effort that went into particular parts of the research (see Chapter 2, Chapter 4 and Chapter 5).

approach adopted in this dissertation (Section 1.6), and a short summary of the dissertation's contributions (Section 1.7).

1.2 Social movements, collective action and social media: The state of the art

1.2.1 Defining social movements and positioning individuals and organizations within social movements

The study of social movements has a longstanding tradition in sociology that dates back to Durkheim's (1912) concept of "collective effervescence" and the Marxian heritage of Habermas (1979, 1987), Touraine (1981), and Calhoun (1982) (for a review of social movements in social theory, see Eder, 2015). Social movement studies are recognized as a scientific, "organizational" (DiMaggio & Powell, 1983) field of investigation and theorizing (Della Porta & Diani, 2015). Nonetheless, the study of social movements has benefited from and expanded thanks to developments in other fields, such as political science, organization studies, and communication science (Della Porta & Diani, 2015). Consequently, the study of social movements is characterized by an interdisciplinary perspective that has produced a variety of definitions of what a social movement is, as well as theories, approaches, and methods to study social movements (for reviews, see, among others, Buechler 2011; Della Porta 2014; Della Porta and Diani 2006, 2015; Eder 2015; Hara and Huang 2011; Johnston 2014; Opp 2009; Snow et al. 2004).

Snow et al. (2004, p. 11) define social movements as "collectivities acting with some degree of organization and continuity outside of institutional or organizational channels for the purpose of challenging or defending extant authority, whether it is institutionally or culturally based, in the group, organization, society, culture, or world order of which they are a part." As collectivities, social movements are sets of individual and organizational actors seeking social change via collective action (Della Porta & Diani, 2015; Diani, 2000, 2003; Snow et al., 2004), that is, through goal-directed activities involving multiple actors in pursuit of a common goal (Olson, 1968). Examples of collective action are social movement campaigns advocating for social causes, for example, those related to health, environmental sustainability, or human rights.

Scholars have long understood movements as having a certain degree of organization (Della Porta & Diani, 2006; Snow et al., 2004; Tarrow, 1998). In fact, many social movements include formal organizations, called social movement organizations (SMOs). SMOs are dedicated to fostering social change on behalf of a constituency (people or groups) and operate to pursue a common goal, to empower, to motivate, and to organize the movement's individual adherents and members by fostering the formation of a collective identity, framing the causes, representing concerns, and operating tactical decisions (McCarthy & Zald, 1977; Snow et al., 2004; Tarrow, 1998). For some scholars,

especially exponents of the resource mobilization theory (McCarthy & Zald, 1973, 1977), SMOs are actors that play a pivotal role in the success of social movements (for a recent review of SMOs and the current state of the art, see Walker & Martin, 2018).

However, the study of social movements is not only about organizations but also about individuals (Della Porta & Diani, 2015). Many scholars take a micro-perspective and investigate the role of individuals within social movements (for a review, see Eder 2015). It has been argued that the success of SMOs and social movements is related to the extent to which individual adherents mobilize (Bimber et al., 2012; Della Porta & Diani, 2006; Tindall, 2004), and how SMOs sustain individual participation by fostering collective identity processes strengthening commitment (Polletta & Jasper, 2001) and the formation of networks of active relationships with movement adherents and members (Diani & Della Porta, 2006; Tindall, 2004). Social movements are “networks of informal relationships” between organizational and individual actors “who share a distinctive collective identity, and mobilize resources on conflictual issues” (Diani, 2000, p. 387). Therefore, looking at micro- or individual-level mobilization dynamics is important to understand social movements and their outcomes.

1.2.2 The advent of social media and the effectiveness of online social movement campaigns

The spread of Internet-based communication technologies, including social media like Facebook and Twitter, has challenged the practices of collective action and the role of individuals and organizations within social movements (Bennett & Segerberg, 2012, 2013; Bimber, Flanagin, & Stohl, 2005; Bimber et al., 2012; Della Porta & Diani, 2015; Earl et al., 2014; Earl, Hunt, Garrett, & Dal, 2015; Earl & Kimport, 2011; Gerbaudo & Treré, 2015; Hara & Huang, 2011; Tufekci & Wilson, 2012). Social media provide free and open platforms to organize, coordinate, and communicate about collective action in fast and cheap ways (Bennett & Segerberg, 2012, 2013; Bimber et al., 2005, 2012; Earl et al., 2014; Earl & Kimport, 2011; Hara & Huang, 2011; Van Laer & Van Aelst, 2010). As the examples in the Preface (Section 1.1.) show, social media contribute to making a campaign go viral or a social movement spread worldwide. Social media facilitate the direct engagement and participation of individuals in collective action as they provide people with personalized media affordances to directly organize, mobilize, and communicate (Bennett & Segerberg, 2013, 2015). In other words, individual agency has become important in the organization and outcomes of collective action by online means, and the success of SMOs and their online campaigns might depend on the extent to which individuals mobilize to support them (Bimber et al., 2012; Della Porta & Diani, 2006; Tindall, 2004). Social media challenge the role of SMOs as critical actors in collective action because social movements by online means might not need strong organizational

structures to achieve their goals (Bennett & Segerberg, 2012, 2013; De Bakker, Hond, & Laamanen, 2017; Dolata & Schrape, 2016; Earl, 2015; Earl et al., 2015; Earl & Kimport, 2011). To address the changing nature of online mobilization, some scholars have coined the term “connective action” in opposition to collective action to emphasize that, in order to mobilize, individuals only have to be connected with each other through networks without explicitly constructing a collective identity (Bennett & Segerberg, 2012, 2013). Social media become the “organizing agents” of connective action (Bennett & Segerberg, 2012, 2013), and SMOs progressively lose their role as necessary actors in mobilization, which becomes a form of “organizing without organizations” (Shirky, 2008). Nonetheless, while there is no doubt that we are witnessing an increasing “organization-less collective action” (Benkler, 2006; Shirky, 2008), SMOs are not disappearing. On the contrary, they are increasing (Bimber et al., 2012) and largely incorporate and use social media to mobilize people and organize campaigns (Bimber et al., 2012; Karpf, 2012, 2018; Kreiss, 2012; Lovejoy & Saxton, 2012; Murthy, 2018). Consequently, SMOs provide people involved in the movement with new ways to engage and participate in collective action via social media.

The question that is still unanswered is whether these new forms of activism, such as online social movement campaigns, are actually effective at achieving their goals by translating online action into meaningful (offline) action. Some scholars and opinion-makers have criticized online activism as “slacktivism,” that is, a weak and lazy form of activism requiring little effort (e.g., a simple “click” or “like”) and rarely fostering actual change or translating into concrete, meaningful action (Gladwell 2010; Kristofferson 2014; Lewis 2014; Morozov 2009). Nonetheless, there are examples of successful online activism, as shown in the Preface (Section 1.1). Academic research also reports several successful cases, such as the campaigns run by the nonprofit organization MoveOn (e.g., Bimber et al., 2012; Eaton, 2010; Hara & Estrada, 2005; Karpf, 2012, 2018), online protests targeting firms, such as Greenpeace’s campaigns against Shell (e.g., van den Broek, 2016), online petitions websites (e.g., Vaillant Gonzalez et al., 2015), and the formation of online social movement communities that allow geographically dispersed activism to grow very rapidly and achieve social change (e.g., Caren, Jowers, & Gaby, 2012). It is clear that we are confronting contrasting positions between scholars wondering about the effectiveness of online activism (e.g., Aral, 2012; Bail, 2016; Calenda & Meijer, 2009; Earl, 2015; Earl et al., 2014; Elliott & Earl, 2018; Fussell Sisco & McCorkindale, 2013; Jones, Soler-Lopez, Zahra, Shankleman, & Trenchard-Mabere, 2013; Koskan et al., 2014; Lovejoy & Saxton, 2012; Maher et al., 2014; Vaillant Gonzalez et al., 2015).

In mobilization contexts characterized by the pervasive presence of social media, increasing individual agency, and organizations that try to adapt to changes in the practices

of collective action, it becomes important to take a micro-level perspective and investigate how people participate in and experience collective action, how individual-level factors impact collective action and SMOs, and how the interactions of individuals lead to collective and organization-level outcomes (e.g., Bimber et al., 2012; Eder, 2015; Milan, 2015; Polletta, 2006; Volpi & Jasper, 2018). By focusing on individual-level mobilization dynamics, this dissertation answers the call for more research on the effectiveness of online social movement campaigns.

1.3 Research problem, research question, and conceptual definitions

The advent of social media has offered numerous opportunities for social movements to mobilize people for social change, such as health advocacy campaigns. However, little is known about how effective online social movement campaigns are at generating social change by translating online action into meaningful (offline) action. In this dissertation, I examine the *effectiveness of online social movement campaigns* by investigating the *micro-mobilization dynamics* relevant to individual participation. More formally, this dissertation answers the question:

How and why do micro-mobilization dynamics explain the effectiveness of online social movement campaigns in achieving social change?

My primary focus is on individuals and how they contribute to the organization and outcomes of social movements' campaigns by participating via online (e.g., social media activity) and offline (e.g., events) means. Thus, my unit of analysis is individuals who participate in campaigns organized by SMOs. Throughout the dissertation, I refer to individuals as *participants* in online social movement campaigns, *adherents* to the movement, and *members* of the SMO.³ SMOs are treated here as the *organizing agents*, or *initiators*, of online campaigns to achieve goals related to the movement's mission.

I define *online social movement campaigns* as collective events aimed at social change, organized by SMOs via social media, and occurring within a finite period of time (Lubitzow, 2013; Marwell & Oliver, 1984; Tilly, 2006). Social media, and Twitter in particular, provide a free and open platform for the organization and coordination of campaigns. They enable direct communication processes between movements and their adherents and provide the means for identity expression, formation, and development that are essential to mobilization. In addition, social media offer a useful data source to understand social

³ The movement's membership is understood as free membership in an SMO but implies the act of freely registering as members of the movement. In this dissertation, I use the terms *campaign participants*, *movement adherents*, and *movement members* interchangeably to refer to my unit of analysis.

phenomena on a large scale (see Section 1.5). Thus, social media provide the context to study new forms of collective action and their effectiveness, and the role of people experiencing collective action within SMOs.

In studying the *effectiveness of online social movement campaigns* at achieving the desired social change, I pay particular attention to the relation between online and offline mobilization, as well as the translation of online individuals' action into concrete and meaningful (offline) action (Bennett & Segerberg, 2012; Earl et al., 2014; Earl & Kimport, 2011; Van Laer & Van Aelst, 2010). To achieve social change, people use sets of means, called "action repertoires" (Tilly, 1984), that can be both supported by online means and created directly online (Van Laer & Van Aelst, 2010). In this dissertation, I track and link how movement members mobilize online and offline by examining action repertoires that combine online and offline elements, such as social media activity, online-supported fundraising for social causes, and the organization of offline events.

To explain the *effectiveness of online social movement campaigns*, this dissertation focuses on *micro-mobilization dynamics*. I define *micro-mobilization dynamics* as the micro-structural and social-psychological *dimensions* and related *processes* that play a role in mobilizing movement members (Della Porta & Diani, 2015; Elliott & Earl, 2018; Snow et al., 2004). *Dimensions* are the "characteristic aspects" of individual mobilization, such as collective identity or social networks, whereas *processes* pertain to how such *dimensions* "evolve and change over the course of movements' operation" (Snow et al., 2004, p. 12). In this dissertation, I look at four key *micro-mobilization dynamics* at play during *online social movement campaigns*: identity, networks, framing, and emotions.

In the next section, I will present the research sub-questions that are addressed in this dissertation.

1.4 Micro-questions for micro-dynamics of individual mobilization

In this dissertation, I investigate four micro-structural and social-psychological dimensions of individual mobilization, namely identity, communication networks, framing and emotions, and related processes, that is, how they evolve and change during mobilization (Figure 1.1).

The first micro-dynamic addressed in this dissertation is identity. As I will further clarify in Chapter 2, identity is a multifaceted concept that has been defined in multiple ways in the literature. Identity not only addresses the strictly individual definition of who someone is (individual identity) but also refers to self-definitions related to identification with others in terms of membership(s) in social categories or groups (social identity) and, more

Figure 1.1. Dissertation Outline. Micro-dynamics in online social movement campaigns.

broadly, highlights ‘we-ness’ and ‘collective agency’ (collective identity). The study of identity as an important dimension of collective action has a longstanding tradition in social movement research (Della Porta & Diani, 2006, 2015; Earl et al., 2014; Earl & Kimport, 2011; Flesher Fominaya, 2010; Snow et al., 2004). Identity is not a static trait of an individual but rather implies a dynamic process (Melucci, 1995) because it evolves and changes over the course of mobilization. Since the start of large-scale waves of mobilization in 2011 characterized by the pervasive use of communication technologies, the role of identity in the study of collective action has been a source of contention (for reviews, see Bakardjieva, 2015; Earl et al., 2014; Earl & Kimport, 2011; Gerbaudo & Treré, 2015). Scholars argue that computer-mediated communication (CMC) – and social media in particular – has changed the construction, maintenance, and negotiation of identities in collective action (see e.g., Della Porta & Diani, 2006; Earl et al., 2014). To take action, individuals only need to be connected with each other through networks without explicitly constructing a common identity (Bennett & Segerberg, 2012). To shed light on this debate, Chapter 2 systematically reviews and synthesizes empirical social science research on identity and collective action via CMC. Notably, the focus is on the role of identity in collective action and CMC’s impact on identity processes during collective action. Chapter 2 answers the following research questions:

Question 2.1: Which concepts, methodological approaches, and perspectives are used in the literature on identity and collective action via computer-mediated communication?

Question 2.2: What are the main findings from the literature on the role of identity in collective action and computer-mediated communication's impact on identity processes?

Chapter 2 concludes by presenting avenues for future research and proposing the adoption of an integrative approach that combines the study of identity and networks to advance our understanding of collective action via computer-mediated communication. The use of an identity-network approach characterizes some of the empirical chapters (3, and 5), which focus on identity and networks as micro-mobilization dynamics at work in online social movement campaigns.

The empirical research of this dissertation (Chapters 3 – 6) is based on an analysis of the Movember Foundation and its US campaign to promote men's health. Started by two friends in Australia in 2003, the Movember Foundation is a global men's movement. The foundation runs yearly campaigns in November in 21 countries by using social media. Its goals are to achieve change in men's health by promoting conversation about and awareness of prostate and testicular cancer, mental health, physical inactivity, and suicide prevention and to raise funds for medical research and men's health programs. The Movember Foundation aims to engage people by welcoming them as members of the movement, called *MoBros* and *MoSistas*, via a free membership. The foundation motivates people to participate and take action by growing a moustache, which is the symbolic collective identifier of the movement, raising awareness and conversation via personal storytelling in social media, organizing offline events to bring men's voice to the street, and engaging in fundraising to collect donations.

Chapter 3 focuses on communication networks generated by movement members during the campaign and the formation of a collective identity. The study of networks in collective action has a strong tradition in social movements studies (e.g., Diani & Della Porta, 2006; Diani & McAdam, 2003; Marwell, Oliver, & Pahl, 1988; McAdam, 1986; Snow, Zurcher, & Eklund-Olson, 1980; Tindall, 2004). When people use social media during campaigns, they create relations with others via communication processes, which produce communication networks (Freeman, 1979; Friedkin, 1991; Wasserman & Faust, 1994). Such networks provide opportunity structures facilitating (or constraining)

individual mobilization (González-Bailón, Borge-Holthoefer, & Moreno, 2013; González-Bailón & Wang, 2016). At the same time, they shape and sustain the collective identity of the movement (e.g., Ackland & O’Neil, 2011; Diani & McAdam, 2003; Monterde, Calleja-Lopez, Aguilera, Barandiaran, & Postill, 2015). However, little is known about the temporal evolution of online networks, and how such networks characterize mobilization dynamics and outcomes, the diffusion of movements, and the emergence of collective identities. Studying the temporal evolution of communication networks in which movement members are embedded is important because it makes it possible to understand the role that online networks play in social movements (Barberá et al., 2015; Diani & McAdam, 2003; González-Bailón & Wang, 2016). In addition, network structures and the resulting collective identity offer means to achieve mobilization outcomes beyond the mere volume of communication produced during the campaign, such as fundraising for social causes. By combining social movement theory and network theory, Chapter 3 addresses the following three research questions:

Question 3.1: How do online communication networks (a) structurally and (b) socially evolve over time in social movement campaigns?

Question 3.2: How do online communication networks shape and sustain the collective identity of the movements over time?

Question 3.3: What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

Chapter 4 is a methodological chapter illustrating the development of automatic tools to detect Twitter users’ social identity. This chapter combines social identity theory, natural language processing, and machine learning to detect individuals’ social identity on the basis of how they describe themselves in their profile description. Chapter 4 answers the following research question:

Question 4: To what extent can the social identity of Twitter users be predicted based on their profile description?

Chapter 4 offers methodological tools (social identity classifiers) for social scientists to scale up online identity research to massive datasets derived from social media. A practical application of the social identify classifiers is shown in Chapter 5.

Chapter 5 focuses on social identity and communication network positions to explain individual mobilization outcomes in online social movement campaigns. Several scholars

have argued in favor of combining motivational and structural factors to understand the mechanisms driving people's engagement in collective action via social media (Gerbaudo & Treré, 2015; Hacıyakupoglu & Zhang, 2015; Kende, van Zomeren, Ujhelyi, & Lantos, 2016; LeFebvre & Armstrong, 2016; Thomas et al., 2015, Chapter 2 of this dissertation). While social identity provides people with motivation to participate in campaigns (van Zomeren, Postmes, & Spears, 2008), occupying a certain position in the communication network provides opportunities to mobilize (Bennett & Segerberg, 2012; Bimber et al., 2005; González-Bailón & Wang, 2016). By using social identity theory and network theory, Chapter 5 offers a statistical test of the effects that movement members' online social identity and structural position in the communication network have on individual mobilization outcomes that require a certain effort, such as collecting donations for medical research. This chapter answers the question:

Question 5: How and why do movement members' online social identity and structural position in the communication network influence the individual amount of collected donations during online campaigns?

The last two micro-mobilization dynamics analyzed in this dissertation pertain to framing and emotions. Social movement research has a longstanding tradition investigating how framing and emotional involvement emerging from interactive and communicative processes among movement members influence participation in collective action (for recent reviews, see Bail 2012, 2016; Cornelissen and Werner 2014; Polletta and Ho 2006; Vasi et al. 2015). The concept of a "frame" is derived from the work of Goffman (1974, p. 11), who defines frames as "principles of organization which govern the subjective meanings we assign to social events." Collective action frames are "interpretative packages" that SMOs use to mobilize potential adherents (Polletta & Ho, 2006). SMOs widely use social media to promote framing processes (Ackland & O'Neil, 2011; Choi & Park, 2014; Harlow, 2012; McCaughey & Ayers, 2003; Pickerill, 2009), draw people's attention to their cause (Bail, 2016), and create discursive opportunities for collective action (Bail, 2016; Vasi et al., 2015). Hence, the first question of Chapter 6 is:

Question 6.1: How does the dominant framing of social movement organizations characterize movement members' discourse in social media during campaigns?

An important precondition for SMOs' framing processes to succeed in mobilizing adherents is "frame alignment," namely, "the linkage of individual and SMO interpretive orientations, such that some set of individual interests, values and beliefs and SMO

activities, goals, and ideology are congruent and complementary” (Snow, Rochford, Worden, & Benford, 1986, p. 464). Movement members contribute to framing processes (Benford & Snow, 2000; Cornelissen & Werner, 2014; Kaplan, 2008; Polletta, 2006; Polletta & Ho, 2006) by both embracing the movement’s dominant frame (Benford & Snow, 2000) and reframing, reinventing, and improvising definitions, language, and symbols (Luna, 2017; Polletta, 2006; Rao, 2009; Snow & Moss, 2014). At the same time, the display of emotions in framing processes is found to trigger “worthiness, unity, and commitment” during mobilization (Tilly, 1994, 1999, 2003, 2004). Chapter 6 uses theories of framing, authenticity, communication, and emotions to investigate the effects of framing adoption and emotional involvement in framing processes and their effects on individual mobilization outcomes, such as collecting donations for medical research. Hence, the second research question of Chapter 6 is:

Question 6.2: To what extent do a) movement members’ adoption of the movement’s dominant framing and b) the level of emotional involvement in members’ framing processes affect movement members’ fundraising outcomes during online campaigns?

1.5 Twitter as data: The Twitter #datagrants project on cancer awareness campaigns

To answer the research questions of this dissertation, I study online social movement campaigns on Twitter. The rise of social media has offered rich, large-scale, longitudinal data sources to study social phenomena (Lazer et al., 2009; Nguyen, 2017; Steinert-Threlkeld, 2018). In this line, the field of computational social science offers approaches to collect and analyze large datasets for social science research (Lazer et al., 2009). Among various social media, Twitter has been widely used in academic studies because it represents the ideal platform to conduct research (for a recent review of Twitter as a data source and the academic research using Twitter, see Steinert-Threlkeld, 2018). Twitter is one of the largest social networking sites with a global reach and offers lots of data that are relatively easier to obtain than on other platforms such as Facebook (Steinert-Threlkeld, 2018). Twitter data takes the form of text, networks, and spatial information: It is suitable to computationally analyze large corpora of text, to build social networks, and to map people’s behaviors and activities (Steinert-Threlkeld, 2018). In this vein, I consider Twitter a data source that, beyond the data, also offers opportunities to develop new methods for social science research and theory development. In fact, the research presented in this dissertation uses a mixed-method approach that combines traditional qualitative and quantitative methods in social sciences, such as networks analysis, content

analysis, and statistical analysis, with machine learning, natural language processing, automated text analysis, and sentiment analysis.

This dissertation focuses on social movement campaigns on Twitter as part of the Twitter #datagrants project of the University of Twente investigating the diffusion and effectiveness of cancer awareness campaigns, such as Movember (prostate and testicular cancer), Pink Ribbon (breast cancer), and SunSmart (skin cancer). Twitter data was provided by Twitter, which introduced the Twitter #DataGrants pilot program in 2014 with the aim of granting a small number of research institutions access to public and historical data.⁴ This dissertation uses data from this project by focusing on one specific campaign (Movember) that represents the context of the empirical chapters, as explained in Section 1.4. The unfettered access to the Twitter archive, combined with additional data on movement members provided by the Movember Foundation, provides a unique opportunity to study the effectiveness of online cancer awareness campaigns by tracking and linking online and offline individual-level data.⁵

1.5.1 Ethical approval to conduct research using social media data

The advent of social media data research has raised new ethical questions and challenges for evaluating the approaches of research protocols (for reviews and discussions, see boyd & Crawford, 2012; Markham, Tiidenberg, & Herman, 2018; Moreno, Goni, Moreno, & Diekema, 2013; Sax, 2016; Shilton & Sayles, 2016; Zimmer & Proferes, 2014)⁶. One of the main issues concerns the debate on whether online social media data should be regarded as public or private. Although academic research has always relied on the use of public data, social media have challenged the concept of privacy because while the social media content is publicly accessible and visible online, this does not imply that it can be used by anyone (boyd & Crawford, 2012). To take care of privacy, informed consent, and related ethical issues, all data used in this dissertation are treated as public data for which Movember and Twitter users gave their informed consent at the time of registration on the Movember website and on Twitter, respectively. All studies included in this dissertation have received approval from the BMS (Behavioral Management and Social Sciences) Ethics Committee of the University of Twente.⁷ For replication reasons, the data

⁴ For more information about the Twitter #DataGrants pilot program, see https://blog.twitter.com/engineering/en_us/a/2014/twitter-datagrants-selections.html.

⁵ *Acknowledgements*: Thanks to Twitter for providing the Tweets as part of their DataGrant program, and Movember for the donation data.

⁶ “danah boyd”, styled in lowercase, is the legal name of the author. Through the dissertation, the author’s name is maintained in that style.

⁷ Reference numbers ethics approvals: 17601 (Chapter 3), 17094 (Chapters 4 and 5), 18013 (Chapter 6).

used in this dissertation are stored as anonymous data in the UT datalab archive of the University of Twente.

1.6 Scientific approach: Embracing multidisciplinary research

The scientific approach adopted in this dissertation is to conduct research with a societal impact by connecting the creation of knowledge with possible practical applications or solutions to social problems (Giebels, Need, & Mouthaan, 2014). Some scholars call this approach “engaged scholarship” and define it as a “participative form of research for obtaining the advice and perspectives of stakeholders (researchers, users, clients, sponsors and practitioners) to understand a complex social problem” (Van de Ven, 2007, p. ix). Research of this type needs to identify common ground between disciplines and combine social and technology domains: Technologies, such as social media, can provide means of communication aimed at the way people organize and manage themselves, have implications to solve social problems, offer methodologies for doing social science research, and serve as a tool for theory development (Giebels et al., 2014). This dissertation starts from a social problem (cancer) that calls for social change and analyzes what actions people and organizations take (social movements, campaigns) to solve the problem and how technologies (social media) can be used as a possible way to find solutions to the problem.

This dissertation originated with the Tech4People program sponsored by the University of Twente, whose aim is to promote projects that combine social sciences with technical and natural disciplines.⁸ In this vein, I purposely adopted a multidisciplinary approach to study cancer awareness campaigns on Twitter. The multidisciplinary approach in theory and methods used in this dissertation, as described in Sections 1.4 and 1.5, is reflected by the motivation, formulation, framing, and evaluation of the various studies presented, as well as the Twitter #datagrants project in which this dissertation is situated.

The multidisciplinary approach adopted in this dissertation suits the pluralist approach of social sciences dealing with the search for the commensurable knowledge (e.g., Della Porta, 2014; Della Porta & Keating, 2008; Gioia & Pitre, 1990). In this view, the social sciences are not dominated by one exclusive paradigm defining what to study and the existence of a real world (ontology), why to study and the possibility to know this world (epistemology), nor how to study and the technical ways to study this world (methodology) (Kuhn, 1962). Instead, social science is

⁸ For more information on the Tech4People project, see Giebels, Need, and Mouthaan (2014).

“non-paradigmatic, in that there can never be one hegemonic approach and set of standards, but that the social world is to be understood in multiple ways, each of which may be valid for specific purposes; or even that it is multiparadigmatic, with different paradigms either struggling against each other or ignoring each other. (...) it is possible to encompass much of the field, not by imposing a single truth, but by setting certain standards of argumentation and debate while recognizing that there are differences in approaches and types of evidence. Although these do not inevitably constitute fundamentally different world views, they are not necessarily all compatible. Researchers need to be aware of the various approaches, the differences among them, and the extent to which they can be combined.” (Della Porta & Keating, 2008, pp. 20–21)

The adoption of a multidisciplinary approach also suits the study of online social movement campaigns and, more broadly, social movements, which requires “cross-fertilization” in theories and “methodological pluralism” (Della Porta, 2014; Della Porta & Diani, 2006; Walker & Martin, 2018).

The work presented in this dissertation benefited from multidisciplinary collaborations with social and computer scientists, as shown in Chapter 4, which presents the development of an automatic tool to detect Twitter users’ identity based on their profile description. Published in the proceedings of the *Empirical Methods for Natural Language Processing* conference, this chapter provides an example of how bridging theoretical approaches and methods from different disciplines can be beneficial in multiple ways. This chapter shows how social theory can be used to guide natural language processing methods and how such methods provide input to revisit traditional social theory that is strongly consolidated in offline settings. In addition, this study offers text classification tools for social scientists to analyze large social media datasets.

The multidisciplinary nature of this dissertation has been welcomed by journals and conferences that fit – or, at least, are open to – such a multidisciplinary perspective. For instance, Chapter 2 has been published in *New Media & Society*, a journal that openly declares its multidisciplinary perspective,⁹ and Chapter 5 is based on work presented at conferences in the fields of sociology (American Sociological Association Annual Meeting), management studies (Academy of Management Annual Meeting), and health and technology studies (HealthByTech, a conference organized by a consortium of research groups in Dutch universities that studies how technology supports health). Work related to Chapter 3 was presented at both specialized (Sunbelt International conference

⁹ For details about the journal’s aim and mission, see <https://uk.sagepub.com/en-gb/eur/journal/new-media-society#aims-and-scope>.

on Network Analysis) and more generic conferences (American Sociological Association Annual Meeting).

1.7 Brief summary of the contributions

Owing to its multidisciplinary approach, this dissertation offers theoretical contributions at the intersection of several fields of studies on social movements, social networks, media and communication, nonprofit organizations, and public health. Methodologically, the empirical work presented in Chapters 3 through 6 exploits the potential of Big Data and computational methods by utilizing a unique dataset provided by Twitter to study the effectiveness of cancer awareness campaigns. This dissertation offers innovative applications and tools for social science research using social media, new ideas on how to use and combine existing methods, techniques, and software to analyze large datasets, and direct access to scripts, codes, and tools developed to support data collection, preparation, and analysis. Appendix F at the end of the dissertation provides a guideline to an online repository containing all the scripts used in this dissertation.

In practical terms, the body of work presented in this dissertation provides multiple organizations (e.g., social movements, health advocacy, nonprofit) with valuable insights into the effective organization of online campaigns via social media. In addition, results from this dissertation can support policymakers and practitioners in framing policies that improve public health via voluntary online fundraising; and individual activists in organizing collective action to produce effective social change in a society characterized by the pervasive influence of social media.

Chapter 2

Identity and collective action via computer-mediated communication: A review and agenda for future research

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Abstract

Since the start of large-scale waves of mobilization in 2011, the importance of identity in the study of collective action via computer-mediated communication (CMC) has been a source of contention. Hence, our research sets out to systematically review and synthesize empirical findings on identity and collective action via CMC from 2012 to 2016. We found that the literature on the topic is broad and diverse, with contributions from multiple disciplines and theoretical and methodological approaches. Based on our findings, we provide directions for future research and propose the adoption of an integrative approach that combines the study of identity and networks to advance our understanding of collective action via CMC. This review contributes to the crossroad of social movement, collective action, communication and media studies. Our results also have practical implications for the organization of collective action in a society characterized by the pervasive influence of CMC.

2.1 Introduction

Since 2011, movements like the Arab Spring, Occupy Wall Street and Movember have gained a global presence, thanks to the massive use of computer-mediated communication (CMC). In this context, the role of identity in the study of collective action has been a source of contention (for a review, see, for example, Bakardjieva, 2015; Earl et al., 2014; Earl & Kimport, 2011; Gerbaudo & Treré, 2015). Scholars from different domains consider identity important to collective action because it explains the coherence and organization of collective actors using CMC to construct their identity and to mobilize (Bakardjieva, 2015; Gerbaudo & Treré, 2015). For example, advocacy campaigns such as Movember or Pink Ribbon, which aim to raise awareness about cancer prevention, use symbols (e.g. a moustache or a ribbon) and pose challenges (e.g. do some sport) to make people identify with the cause and construct a collective identity in order to foster participation in the campaign activities (e.g. fundraising, social events).

Various scholars acknowledge that CMC has changed the construction, maintenance and negotiation of identities in collective action (see, for example, Earl et al., 2014; Earl & Kimport, 2011; Milan, 2015; Russell, 2005; Stein, 2009; Wall, 2007). For instance, social networking sites like Twitter offer the space and means to quickly, easily and often creatively express, construct, share and negotiate the identities that become symbols of protest movements or advocacy campaigns.

However, some scholars argue that the role of identity in collective action via CMC is less relevant since the emergence of 2011 networked movements (e.g., Bennett & Segerberg, 2012; Loader & Mercea, 2012). New mobilization forms via CMC are considered ‘connective’ rather than ‘collective’: To take action, individuals only need to be connected with each other through networks without explicitly constructing a common identity (Bennett & Segerberg, 2012). These claims have moved scholars interested in identity to call for research on the ‘conceptual and methodological underpinnings’ of how such identities are transformed in the digital era (Gerbaudo & Treré, 2015, p. 870; Milan, 2015) and affect collective action via CMC, in particular by looking at the interaction between identities, networks and media structures (Bakardjieva, 2015; Earl et al., 2014; Earl & Kimport, 2011).

Following up on these calls, our research sets out to systematically review and synthesize empirical studies on identity, collective action and CMC since 2011, considered a landmark year in the emergence of the biggest networked movements. In reviewing the articles, we focus on the role of identity in collective action and CMC’s impact on identity processes during collective action. We answer two main research questions by conducting a descriptive analysis and a thematic analysis:

Question 2.1: Which concepts, methodological approaches, and perspectives are used in the literature on identity and collective action via computer-mediated communication?

Question 2.2: What are the main findings from the literature on the role of identity in collective action and computer-mediated communication's impact on identity processes?

We offer three main contributions. First, we respond to existing calls for the development of a research agenda regarding the interplay between identity, collective action and CMC (Bakardjieva, 2015; Gerbaudo & Treré, 2015) by developing conceptual and methodological research directions. In this way, we advance multiple research fields (e.g. social movements, collective action, media and communication) by systematically synthesizing key concepts, perspectives, methods and findings to better understand the role of identity in collective action and the circumstances under which CMC influences identification processes during collective action.

Second, we propose an integrative approach combining the study of identity and networks to address the research directions that the agenda proposes. Thereby, we not only improve our understanding of collective action via CMC but also provide more theoretical nuance and synthesis to the concept of identity in a largely multidisciplinary domain.

Third, we show the practical implications of studies on identity, collective action and CMC. Activists not only construct and develop new identities via CMC but also exploit CMC to organize, coordinate and communicate about collective action to achieve social change.

2.2 Defining the key concepts

In this section, we provide definitions of the key concepts guiding the review: identity, collective action and CMC.

2.2.1 Identity

Identity is a multifaceted concept that has been defined in many ways due to its application in various disciplines (Flesher Fominaya, 2010). Some scholars (e.g., Snow, 2001) argue for the necessity of distinguishing between different types of identity that, while they might overlap, have distinct characteristics. For example, *individual* or *personal identity* is a self-definition based on individual internalized attributes and meanings (Snow, 2001; Stets & Burke, 1994). While there is consensus that this type of identity is different

from social or collective identities because it is personally distinctive, an individual identity can be interconnected with social and collective identities (Gamson, 1991; Polletta & Jasper, 2001; Snow, 2001).

Social identity expands the definition of the self from the personal 'I' to 'others and I'. Social identification with others can be derived from membership(s) to social categories (e.g. teams, organizations, ethnicity, political affiliation), as expressed in social identity theory (Tajfel & Turner, 1979; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). More recent research in social psychology indicates that social identity refers to the identification with social groups, such as opinion-based groups (Bliuc, McGarty, Reynolds, & Muntele, 2007; McGarty, Thomas, Lala, Smith, & Bliuc, 2014). Other definitions derived from identity theory feature self-definitions based on social roles, such as being a mother or a doctor (e.g., Snow, 2001; Stryker, Owens, & White, 2000).

Collective identity, by contrast, highlights 'we-ness' and 'collective agency'. The former makes people aware of being part of a group, and the latter fosters action towards common goals (Snow, 2001). Collective identity is a process that involves cognitive definitions of such goals and means of action, networks of relations between individuals who interact with each other, and a certain emotional investment that contributes to a sense of common unity (Melucci, 1995). According to some scholars, collective identity differs from social identity as it denotes a higher level of identification with a certain social group (see Snow, 2001 for details).

Despite the differences between individual, social and collective identities, it is acknowledged that scholars have lost sight of such a distinction (Flesher Fominaya, 2010). It seems difficult to distinguish clearly between social and collective identities in social psychology (e.g., McGarty et al., 2014) and social movement literature (e.g., Bobel, 2007; Opp, 2009) because the two concepts are considered to be overlapping definitions of group identification and essentially the same concept but seen from different perspectives.

In this review, we differentiate between individual, social and collective as 'identity types' to characterize and delineate the various analytical labels and to distinguish how authors use them in the literature. This differentiation can be seen as a continuum from a micro- to a macro-definition of the self: 'I' (individual), 'others and I' (social) and 'we' (collective). Furthermore, we distinguish between one-type and multiple-type studies. In the one-type studies, research focuses only on one identity; multiple-type studies investigate more than one identity.

In addition, as we consider identity to be a dynamic process rather than a static trait of an individual (Melucci, 1995), we define 'identity phase' as the various stages of such a process. In this review, we distinguish between initial (e.g. expression, formation, building and adoption) and later (e.g. negotiation, maintenance, diffusion) phases.

2.2.2 Collective action

Collective action refers to a collective of individuals who coordinate and act together in order to achieve a common goal or interest (Olson, 1968). Owing to the pervasive influence of CMC in our lives, collective action is increasingly described as a mix of online and offline elements (Bennett & Segerberg, 2012; Earl et al., 2014; Earl & Kimport, 2011; Van Laer & Van Aelst, 2010).

We differentiate between two forms of collective action on the basis of the CMC role. We define ‘CMC-based’ as collective action that takes place online and exists only because of CMC (e.g. online petitions, cyberactivism and hacktivism). By contrast, we define ‘CMC-supported’ as traditional collective action (e.g. street rallies, occupations, fundraising) that takes place offline and uses CMC as a channel to organize and communicate. In this review, we consider both forms of collective action.

2.2.3 CMC

We define CMC as human communication via electronic devices that encompasses all digital technologies (e.g. email, websites, social networking sites and text messaging) that channel and shape communication and social behaviors (Herring, 2004). In this review, we consider CMC in its broader definition to address the variety of means used during collective action (see, for example, Lomicky & Hogg, 2010; Mercea, 2012).

2.3 Methods

Following the method of Tranfield et al. (2003), we conducted a systematic literature review of identity and collective action via CMC to identify, synthesize and integrate the articles’ findings and address directions for future research.

We defined a search query using keywords related to our three key concepts: (identity OR identification) AND (‘collective action’ OR activism OR campaign* OR ‘collective-action’ OR mobilization OR ‘social movement*’ OR ‘social-movement*’) AND (internet OR blog* OR CMC* OR ‘computer-mediated communication’ OR ‘computer mediated communication’ OR digital OR Facebook OR microblogging OR online OR ‘social media’ OR ‘social networking sites’ OR ‘Twitter’ OR web OR ‘Web 2.0’ OR ‘world-wide-web’ OR ‘world wide web’). We searched in Web of Science and Scopus. The selection criterion was empirical articles published in English peer-reviewed journals, books or conference proceedings in the social sciences.

We selected articles published from 2012 to 2016 for two main reasons. First, 2011 is the landmark year of the phenomenon under investigation because this is when various new networked movements (e.g. Arab Spring, Occupy Wall Street) arose and spread

worldwide via social media. Studies published before the 2011 movements wave, in fact, primarily focused on the relation between identity and so-called 1.0 technologies (e.g. emails, blogs and websites) and how they impact on online and offline collective action (for a review, see, for example, Earl et al., 2014; Treré, 2015). From 2011 onwards, the emergence of networked movements has triggered research on the dynamics of new forms of collective and connective action (e.g., Bennett & Segerberg, 2012; Earl & Kimport, 2011; Mattoni & Treré, 2014). Because we wanted to focus on empirical research that followed such phenomena, we chose 2012 as the starting point of our articles' selection. Second, similar reviews had been published before 2012 (e.g., social movements and the information and communications technology (ICT) revolution: Earl et al., 2014; digital activism: Earl & Kimport, 2011; collective identity in traditional social movements Flesher Fominaya, 2010), and our review would have overlapped.

Figure 2.1 shows the flowchart of the selection process. The first search completed in September 2015 resulted in 437 articles. All authors performed manual annotation to assess relevance by title, abstract and full text. The criterion for relevance was that while at least two out of three key concepts (identity, collective action and CMC) had to be present in the title and abstract, all three concepts had to be included in the full text. To ensure reliability, we calculated the proportional reduction in loss (PRL) reliability for qualitative data (Rust & Cooil, 1994). It compares reliability with loss from poor decisions while measuring the proportion of expected loss associated with the judges' lack of agreement. Its range varies from 0 (lack of reliability) to 1 (perfect reliability), and its benchmarks are to be interpreted as for Cronbach's alpha. We obtained good or high scores in all sessions ($PRL_{\text{title}} = 0.93$, $PRL_{\text{abstract}} = 0.78$, $PRL_{\text{full-text}} = 0.82$).

This selection process resulted in 32 articles. Next, we operated a manual search for other relevant articles by checking the references and citations ($N = 35$). The list was updated in September 2016 and resulted in a final set of 59 articles published between 2012 and 2016.

To conduct the review and reduce human error, we used a data-extraction form as a repository for general (title, authors, journal) and specific (concepts, theories, methods, key findings) information related to the review's research questions (Tranfield et al., 2003)¹⁰. We followed a two-stage approach to provide a clear review of the articles (Tranfield et al., 2003). First, we used descriptive analysis to provide an overview of key concepts, methodological approaches and perspectives used in the literature (Question 2.1). Second, we conducted a thematic analysis using an inductive, interpretative approach to report, bring together and synthesize the findings from the existing studies (Question 2.2). We divided the articles according to our two *foci* of analysis: (1) identity as a driver of

¹⁰ The data-extraction form is provided in Appendix A at the end of this dissertation.

Figure 2.1. Flowchart of the selection process.

collective action and (2) CMC's impact on identity processes during collective action. We analyzed the articles by identifying key themes of discussion and related findings, and focusing on the extent to which articles were similar or different in their results (Tranfield et al., 2003).

2.4 Review of the literature

In this section, we present the results of descriptive analysis and thematic analysis to answer our review's research questions.

2.4.1 Descriptive analysis

We used descriptive analysis to summarize the literature in terms of key concepts, methodological approaches and perspectives (Table 2.1).

Table 2.1. Summary of key concepts, methodological approaches and perspectives used in the literature.

Key concepts	Identity	Type ^a	One-type: Collective (46%), Social (34%); Multiple-type: Individual-collective (14%), Individual-social (3%), Collective-social (3%)
		Phase ^b	Expression (19%), Formation (56%), Adoption (2%), Development (3%), Management(2%), Negotiation (7%), Maintenance (7%), Diffusion (3%), Consolidation (2%), Legitimation (2%), Rejection (2%), Social/group/collective identification (24%)
Methodological approaches	Collective action	Form ^a	CMC-based (27%), CMC-supported (31%), Comparison (42%)
			Qualitative (53%), Quantitative (22%), Mixed (25%)
Perspectives^a			Social psychologists (17%), New social movement scholars (17%), Bridging scholars (42%), Other (24%)

CMC: computer-mediated communication.

^aCategories are mutually exclusive (one article can belong only to one category).

^bCategories are not mutually exclusive (one article can focus on more than one identity phase at once).

Identity types and phases. The vast majority of articles were one-type studies on either social (34%) or collective (46%) identity. Multiple-type studies combined only two types, mostly individual and collective (14%). Regarding the identity process, research mainly focused on such a process’ initial phases (expression and framing, 19%; formation, building and construction, 56%). Studies on various forms of identification (social, group, collective) were also quite common (24%). By contrast, analyses on later phases (e.g. negotiation, maintenance, diffusion) were less frequent (<7%).

Forms of collective action. In the literature, we found studies that focused only on one form of collective action (either CMC-based or CMC-supported) or compared the two with each other. Scholars mostly conducted comparative studies (42%) or studied only CMC-supported collective action (31%).

Methodological approaches. Overall, qualitative methods were mostly used (53%), followed by mixed (25%) and quantitative (22%) approaches. Qualitative research was largely applied to one-type studies that focused on collective identity formation. Thematic analysis, interviews and digital ethnography were found to be more common in in-depth analytical approaches to study this phase. Quantitative methods were mostly used in social identity studies because statistical analysis and field experiments proved valuable to investigate the relation between identification processes and collective action. Finally, mixed methods were predominantly used in studies of collective identity expression and formation. This shows an emerging practice of combining different methodologies to

assess both the qualitative nature of identity and the quantitative, network structure of CMC.

Table 2.2. Perspectives identified in the literature.

	Social psychologists	NSM scholars	Bridging scholars	Other
Focus	Psychosocial predictors of collective action	Collective identity as a key component of collective action	Interplay between identity, social movements, network and media structures	–
Theoretical approach	Social identity theory, collective action theory	New social movement theory, collective action theory	Bridging identity theory, social movement theory, network theory and media theory	–
(Main) Method	Quantitative	Qualitative	Qualitative and Mixed	Qualitative
Identity Type	Social	Collective	All	All
Form of action	Collective (behaviours)	Collective	Collective and Connective	Collective

NSM: new social movement.

Figure 2.2. Distribution of the articles per perspective, identity type and methodological approach (N = 59)

Perspectives. In the literature, we identified three main perspectives in which scholars used distinct approaches in theory, methods and analysis: social psychologists (17%), new social movement (NSM) scholars (17%) and bridging scholars (42%). A fourth category, ‘Other’ (24%), included all articles that could not fit into any of the other perspectives.

Table 2.2 provides a summary of each perspective’s main characteristics. Figure 2.2 illustrates the distribution of articles per perspective, identity type and methodological approach. In the literature, we noticed that the labels used to address identity types differed between the perspectives of the scholars. For example, social psychologists focused on social identity theory (Tajfel & Turner, 1979; Turner et al., 1987) and considered social identity one of the main psychosocial predictors of collective action. Social psychology studies were mostly one-type and used quantitative methods. NSM scholars, by contrast, followed in the footsteps of the social movement theory tradition (Gamson, 1992; Melucci, Keane, & Mier, 1989; Polletta & Jasper, 2001; Snow, 2001; Taylor & Whittier, 1992): Using (mostly qualitative) research, they considered collective identity to be very relevant to the study of collective action. Finally, we found that most of the studies could be positioned as a ‘bridge’ linking theories on identity, social movements, networks and media. Although their research was mostly qualitative, bridging scholars explored mixed-methods approaches to study the changing nature of identity in collective action via CMC. We defined the remaining articles that could not be classified in any of the groups above as ‘Other’ because they focused on particular types of identity (e.g. gender, ethnic, national), theoretical approaches (e.g. ethos, self-presentation, gender theories) and disciplines (e.g. linguistics, semiotic, anthropology). These (mostly qualitative) studies show how research on identity and collective action is very diverse and multidisciplinary.

2.4.2 Thematic analysis

In the second stage of our review process, we used thematic analysis to report and synthesize the findings from the existing studies (Question 2.2) according to our two *foci* of analysis: the role of identity in collective action and CMC’s impact on identity processes. Table 2.3 shows the distribution of articles grouped by focus of analysis, identity type and perspective. Figure 2.3 illustrates the synthesis of themes (T) and related findings from the literature.

Table 2.3 Thematic analysis: distribution of articles per focus of analysis, identity type and perspective.

Focus of analysis	Identity type	Perspective			N
		Social psychologists	NSM scholars	Bridging scholars	
The role of identity as a driver of collective action	Social	Alberici and Milesi (2013), Chan (2014), Coppock et al. (2016), Hartley et al. (2016), Kende et al. (2016), Schumann and Klein (2015), Thomas et al. (2015)		Chan (2016), Hacıyakupoglu and Zhang (2015), Hitt et al. (2015), Lefebvre and Armstrong (2016), Seo et al. (2014)	12
	Multiple	Park and Yang (2012), Alberici and Milesi (2016)			2
CMC's impact on identity processes	Social	Smith et al. (2015)		Kharroub, Tamara Bas, Ozen (2015), Ribke and Bourdon (2016); Sanderson et al. (2016)	8
	Collective		Drissel (2013), Flesher Fominaya (2015), Harlow (2012), Leung (2013), Mercea (2012), Pilny and Shumate (2012), Treré (2015)	Beraldo and Galan-Paez (2013), Choi and Park (2014), Coretti, and Pica (2015), Jensen and Bang (2013, 2015), Kavada (2015), McDonald (2015), Penney (2015), Poell et al. (2015), Romanos (2015), Svensson (2012), Vicari (2014)	27
	Multiple		Gerbaudo (2015), Rodan and Mummery (2016), Svensson et al. (2015)	Kavada (2012), Milan and Hintz (2013), Monterde et al. (2015), Ortiz and Ostertag (2014), Soon and Kluver (2014)	10

CMC: computer-mediated communication; NSM: new social movement.

Figure 2.3. Thematic analysis: synthesis, key themes (T) and findings.

The role of identity as a driver of collective action

Research in this area is exclusively one-type (social identity), with the exception of Park and Yang (2012), who conceptualize identity as a combination of individual identity and identification with social groups. Social psychologists study this topic by using traditional social identity theory, while bridging scholars combine identity and media theories. In both cases, the objects of analysis are the psychosocial predictors of collective action: social identity, injustice (i.e. feeling of deprivation) and collective efficacy (i.e. the belief that action is effective for achieving goals). We identify two themes (Figure 2.3, T1 and T2) discussed in the literature and synthesize the main findings for each theme.

First, some authors investigate the role of social identity in new CMC-based forms of collective action – such as online petitions (Earl & Kimport, 2011) – that are often low-cost, low-risk and based on mass participation (T1). The main question is whether identity fosters or constrains these forms of mobilization and if there is a transition offline. Despite such forms of collective action currently being widespread, research on the topic is scant. Furthermore, authors obtain divergent results. On the one hand, some scholars find that online social identities can transform low-threshold online collective action (e.g. tweeting about an online petition) into meaningful online action (e.g. getting the online petition signed) (Coppock, Guess, & Ternovski, 2016). On the other hand, authors argue that if identity consolidation and group enhancement become too strong, they will fail to drive offline collective action (Schumann & Klein, 2015). This happens because strong online group identification fulfils people's need to perform online low-threshold action and then derail offline collective action that would satisfy the same need.

Second, scholars find that identity alone might not be sufficient to predict collective action via CMC (T2). Some authors argue that people's use of CMC maintains an individual's social identification with online groups or communities due to in-group norms for emotion, efficacy and action that are reinforced online (Chan, 2014; Hacıyakupoglu & Zhang, 2015; Hitt, Gidley, Smith, & Liang, 2015; LeFebvre & Armstrong, 2016; Park & Yang, 2012; Thomas et al., 2015), in particular when people use CMC in an interactive way (Alberici & Milesi, 2013; Kende et al., 2016). Consequently, online social identity strengthens people's willingness to participate in collective action on behalf of the group both online and offline. In addition, we find that the type of CMC matters in the effectiveness of identity as a driver of collective action. For example, when comparing social media with traditional media use in protests, Chan (2016) finds that social identification can predict the intention to participate in protest only when people use traditional media, whereas other psychosocial antecedents predict collective action in the case of social media use. Similarly, the role of identity in collective action might depend on the type or structure of collective action (Hartley, Lala, Donaghue, & McGarty, 2016; Seo,

Houston, Knight, Kennedy, & English, 2014). Owing to the massive use of CMC for mobilization, some new forms of collective action, like flash mobs, have characteristics or conditions that do not require strong identification between the participants to make them happen, which confirms what previous literature reviews have emphasized (e.g., Earl & Kimport, 2011).

CMC's impact on identity processes.

Defining identity as a process (Melucci, 1995), we look at the impact of CMC in identity processes during collective action. We found that it is a frequent topic of analysis in both one- and multiple-type studies across all perspectives (Table 2.3). However, scholars obtain divergent results regarding whether or not CMC supports such identity processes (Figure 2.3, T3 and T4).

Studies finding that CMC supports identity processes. Scholars have identified various ways in which CMC can successfully support identity processes (T3). First, CMC provides open, free places for identity expression, formation, consolidation, maintenance and negotiation during collective action. On websites, blogs, forums and social media, identity processes are fostered through icons, symbols, images, narratives and discursive strategies that people use to construct social (Adegoju & Oyeboade, 2015; Anderson & Grace, 2015; Han, 2015; Kharroub & Bas, 2015; Smith, Gavin, & Sharp, 2015) and collective identities (Chiluwa, 2012; Choi & Park, 2014; Drissel, 2013; Jaworsky, 2015; Kavada, 2015; Lengel & Newsom, 2014; MacKay & Dallaire, 2012; Penney, 2015; Svensson, 2012; Treré, 2015). Multiple-type studies show CMC's effectiveness at fostering the transition from individual to collective identities on blogs and social media (Chapman & Coffé, 2015; Gerbaudo, 2015; Ortiz & Ostertag, 2014; Soon & Kluver, 2014). However, research mostly focuses on the identity process' initial stages; studies on later phases remain scant (Drissel, 2013; Soon & Kluver, 2014; Svensson, 2012; Svensson, Neumayer, Banfield-Mumb, & Schossboeck, 2015; Treré, 2015).

Second, research on social and collective identities finds that the openness of CMC gives voice to political (Choi & Park, 2014; Han, 2015) or ethnic groups (Gabriel, 2016; Ribke & Bourdon, 2015; Sanderson, Frederick, & Stocz, 2016) and to online communities (women: Hardaker & McGlashan, 2016; Tanczer, 2015; lesbian, gay, bisexual and transgender (LGBT): Reyes Soriano, 2014) that are struggling to achieve freedom of identity expression in a context of social change.

Third, studies on collective identity demonstrate the effectiveness of CMC in transnational and organizational movements (Kavada, 2012, 2015; Romanos, 2015; Stephan, 2013; Vicari, 2014). CMC offers ways to display transnational identities and fosters the creation of symbols, cross-national solidarity and network interaction used to

facilitate the construction of collective identities. In addition, CMC fosters the formation of solid hyperlinks (e.g. via websites) that facilitate online identification between similar movements and organizations, digital collaboration and mobilization (Harlow, 2012; Pilny & Shumate, 2012).

Fourth, CMC offers opportunities to hide identity, which favors anonymity. Being anonymous in cyberspace is a powerful, effective strategy to ensure the success of activists' goals during protests and revolutions (Gamie, 2012) without running the risk of being publicly identified with the movement (Hardaker & McGlashan, 2016). A frequently cited case study on this topic is the radical tech-group Anonymous (Gamie, 2012; Leung, 2013). Anonymous demonstrates how collective identities emerge from intertwined private and subjective experiences between distinct individuals who act individually before embracing the collective identity of 'We are Anonymous' by recognizing their similarity with other hacktivists (Gerbaudo, 2015; Milan & Hintz, 2013).

Finally, bridging scholars' studies on the role of CMC in identity processes show the changing nature of collective identity and the use of particular identity definitions to take such changes into account. For example, 'network identity' is used to define the identity of emergent networked social movements (e.g. World Social Forum) that have a strong network organizational structure (Vicari, 2014); 'project identity' (Castells, 2011) is associated with activists who seek to build strong solidarity in their networked communities and connectively act together to achieve a shared project or goal (Jensen & Bang, 2015, 2013); 'connective identity' is used to define the identity of the Occupy Wall Street movement, which was reconceptualized by horizontal structures, networking practices, social media communication and consensual decision making (Beraldo & Galan-Paez, 2013); and 'multitudinous identity', associated with the 15M movement in Spain, combines the personal dimension, which is typical of CMC networked individualism and connective action, with collective, dynamic interactions between multiple actors engaged in the movement (Monterde et al., 2015).

Studies finding that CMC does not support identity processes. In the literature, we find studies that demonstrate how CMC does not support identity processes (T4). First, communication protocols, organizational centralization and fragmentation of certain online groups and communities in social media impede the formation of solidarity and strong ties between members, which precludes the development of a collective identity (Coretti & Pica, 2015). Such a failure is due to the lack of fit between social media infrastructures and people's need to act together.

Second, CMC facilitates more organizational activities during collective action (e.g. garnering information, coordinating and promoting mobilization) than symbolic ones,

such as building a collective identity (Mercea, 2012; Poell, Abdulla, Rieder, Woltering, & Zack, 2015). Furthermore, CMC routinization (e.g. sending email is a common practice in our daily lives) can explain why people do not use these tools to build a collective identity (Flesher Fominaya, 2015).

Third, although some research on anonymity has shown the positive role of CMC in fostering identity processes (e.g., Gamie, 2012), other scholars find opposite results. In a case study about Anonymous, McDonald (2015) argues that activists adopt less stable practices of digital collaboration (use of a mask, the grotesque, the ephemeral), which explains action in online cultures more efficiently than identity does. Hiding behind a mask is claimed to be a clear rejection of identity.

2.5 Discussion

Based on the review of 59 relevant articles, we found that empirical research on identity, collective action and CMC is broad and diverse because of contributions from multiple disciplines, theoretical perspectives and methodological approaches. In this section, we summarize the main results by answering our research questions on the concepts, methodological approaches, perspectives used (Question 2.1) and the findings from the literature (Question 2.2). From shortcomings in the findings, we derive directions for future research that address conceptual and methodological aspects. We conclude by proposing an integrative approach combining the study of identity and networks to advance our understanding of collective action via CMC.

2.5.1 Conduct more multiple-type identity research

To answer Question 2.1, we looked at how the concept of identity is used in the literature. We noticed that various definitions of identity types (individual, social and collective) tend to be used, depending on the particular scholar's perspective (Table 2.2). This shows how identity conceptualization stands at the crossroads of various disciplines.

Furthermore, we found mostly one-type studies focusing on collective identity. Although multiple-type studies were not very common, we found examples from all perspectives: social psychologists (e.g., Alberici & Milesi, 2016; Park & Yang, 2012), social movement (e.g., Gerbaudo, 2015; Rodan & Mummery, 2016) and bridging scholars (e.g., Milan & Hintz, 2013; Monterde et al., 2015). These studies show that identity is a multifaceted concept and has to be investigated as such. The importance of studying the nexus between individual, social and collective identities has already been mentioned in previous reviews on identity and traditional social movements (Flesher Fominaya, 2010). As it becomes harder to disentangle these different types of identities in the context of collective action via CMC, we argue that the need to investigate such nexus is even more

pressing. Indeed, networked movements like 15M or forms of hacktivism such as Anonymous are characterized by strong network individualism and identification processes that involve individual, social and collective dimensions of the self. By addressing the urge to synthesize all identity concepts in a reasonable manner and acknowledging how such concepts mirror various perspectives in the literature, we propose to look at identity as the interaction between individual (I), social (the others and I) and collective (we) identities representing a continuum of different but interrelated dimensions of the self. In this way, we call for future research that account simultaneously for the personal dimension of network individualism that is typical of CMC structures and social and collective identification processes that can foster symbolically collective action (e.g., Gerbaudo, 2015; Monterde et al., 2015).

2.5.2 Investigate later identity phases

While answering Question 2.1, we also looked at identity as a dynamic process and found that most research on both social and collective identity focused on initial phases, such as expression and construction. Findings from the thematic analysis (Question 2.2) showed that it is important to study empirically not only how individual, social and collective identities are constructed online but also how they are negotiated over time. Therefore, more research should investigate later phases of the identity process, such as its development, negotiation and maintenance in social groups (social identity) and movements (collective identity) (e.g., Kavada, 2015; Leung, 2013; Svensson et al., 2015).

2.5.3 Examine the conditions under which identity drives collective action via CMC

In this review, we looked at the role of identity as a driver of online and offline collective action (Question 2.2) and found extensive research on the topic. In particular, scholars focused on social identity as a psychosocial motivator of collective action in social psychology and bridging studies. They found that social identity alone might not be enough to predict collective action. They stressed the importance of investigating other conditions (e.g. media use, CMC dynamics, networks, social structure, external institutional factors) under which social identity can drive collective action, including the transition from online to offline mobilization. Although some studies have moved in this direction further research should investigate the mediating or intervening mechanisms that are activated in this process (e.g., Chan, 2016; Kende et al., 2016).

By contrast, little research looked at the role of collective identity as a driver of collective action: Studies on collective identity mainly focused on how CMC affects the identification process during mobilization. Other perspectives (e.g. NSM scholars)

focusing primarily on collective identity could thus unpack the mechanisms under which such an identity type can drive collective action via CMC (e.g., Harlow, 2012; Pilny & Shumate, 2012).

2.5.4 Shed light on the controversial role of CMC in identity processes

In response to Question 2.2, we also looked at how CMC influences identity processes and found extensive research on the topic. These studies showed that, starting with the 2011 wave of large-scale mobilizations, CMC has changed the construction, maintenance and negotiation of both social and collective identities. However, we found divergent results on whether CMC supports or constrains identity processes. While some scholars highlighted CMC's limited success in collective identity formation due to inappropriate communication protocols, organizational fragmentation and routinization, others found that CMC enables symbolic practices and network ties that express and build both social and collective identities.

Future research in all perspectives should address these contradictions by acknowledging the changing nature of social and collective identities during collective action via CMC. CMC's intended role should be not only instrumental (e.g. organizing mobilization) but also symbolic (e.g. expressing and communicating identity processes). The work of bridging scholars can offer several examples in this regard: They have often adopted definitions of identity that simultaneously combine theories on identity, social movements, networks and media structures to tackle the changing nature of online collective identities (e.g., Beraldo & Galan-Paez, 2013; Monterde et al., 2015). However, although some definitions of identity might appear more novel than others (e.g. multitudinous identity, connective identity), future research should resist the urge to coin new definitions that cannot really produce additional value.

2.5.5 Adopt multidisciplinary, mixed-methods approaches

In answering Question 2.1, we looked at the perspectives and methodological approaches used in the literature. First, we found three main perspectives and a broader fourth group showing the variety of approaches and results identified in empirical research. Bridging scholars predominantly conducted multidisciplinary research by combining theories from various domains, such as sociology, social psychology, anthropology, media and communication studies. Thus, more multidisciplinary research might prove valuable to grasp the dynamics between identity and collective action via CMC. For example, combining social psychology theories on identity and media theories might provide a better understanding of the mobilizing potential of social identity through media use (e.g., Chan, 2016). Linguistic, socio-semiotic and discourse studies might offer insight to explore

the dynamic phases of the collective identity process and their interplay with collective action (e.g., Beraldo & Galan-Paez, 2013; Hardaker & McGlashan, 2016). The combination of social movement and organizational communication theories might allow simultaneously taking dynamic collective identity processes, collective action organizational structures and CMC into account (e.g., Kavada, 2015).

Second, we found that methodological approaches varied according to the analyzed identity type. Qualitative methods were preferred in the study of collective identity as they provided tools to focus more in depth on expression and formation phases. By contrast, studies on social identity were mainly quantitative because scholars were interested in explaining the causal relation between social identity and collective action. Mixed-methods research was largely multidisciplinary and not very frequent. We recommend that future studies adopt mixed-methodological approaches to deal with both the necessity of quantitative tools for the analysis of big data coming from CMC platforms and the qualitative need to understand individual, social and collective identities as shared meanings, frames and narratives. For example, combining machine-learning techniques and traditional social science methods might help to deal with the complexity of large datasets from social media (e.g., Jensen & Bang, 2013). As individual, social and collective identities are often expressed in texts and language, quantitative methods might be used to detect emerging discourses and subsequently qualitative methods for more in-depth analysis (e.g., Hardaker & McGlashan, 2016). Data triangulation combining network analysis, quantitative (e.g. statistical analysis, webometrics, randomized field experiments) and qualitative (e.g. digital ethnography, interviews) methods could prove valuable to address the interplay between (individual, social and collective) identity, networks and CMC structures (e.g., Beraldo & Galan-Paez, 2013; Choi & Park, 2014; Monterde et al., 2015).

2.6 Towards an integrative approach of identity and networks

We conclude this review by proposing an approach that can help addressing the conceptual and methodological directions suggested above. We propose combining and integrating the study of (individual, social and collective) identity and networks to advance our understanding of collective action via CMC. The work of bridging scholars offers several examples in this regard (e.g., Beraldo & Galan-Paez, 2013; Milan & Hintz, 2013; Monterde et al., 2015; Vicari, 2014). These authors show how empirical research on identity and networks can grasp identification processes of online groups and communities (social identity) as well as social movements (collective identity) that are characterized by strong network structures, which also foster individualism (individual identity). Such

network structures are not alternative but complementary to social and collective identification processes. Opposing networks to identity and collective action to connective action is counterproductive because they are important dimensions of the same interplay.

The adoption of this integrative approach can also advance our understanding of identity as a multifaceted, dynamic concept by providing more theoretical nuance to and synthesis of the multiple definitions and conceptualizations of identity in a multidisciplinary domain, as the one of collective action via CMC. Starting from our vision of identity as a continuum of interrelated dimensions of the self, future research could put forward theoretical models that grapple with the complexity of the identity concept in the study of collective action via CMC. Furthermore, such an approach can guide empirical research that is insightful and helps practitioners understand how activists construct and develop new (individual, social and collective) identities via CMC and use CMC to organize, coordinate and communicate about collective action to achieve social change.

2.7 Conclusion

Our research set out to systematically review and synthesize empirical studies on identity and collective action via CMC since 2011. From 2011 onwards, the emergence and spread of big network movements via social media increased the discussion of the relevance of identity for collective action. This triggered a new wave of research to investigate the nexus between identity, CMC and new forms of collective action. On the basis of the articles in this review, we found that such empirical research is very broad, comes from various disciplines and adopts different theoretical and methodological approaches. Scholars advanced new theories and conceptualizations to account for the changing nature of (individual, social and collective) identities in the study of collective action via CMC. Methodologically, they explored new venues to combine quantitative and qualitative techniques for the analysis of larger dataset coming from social media.

In this light, we provided directions for future research and addressed conceptual and methodological aspects. Furthermore, we proposed adopting an integrative approach combining the study of identity and networks to advance our understanding of collective action via CMC. Compared to previous reviews on identity and traditional (offline) social movements (e.g., Flesher Fominaya, 2010), our work extended to the online component of collective action. In addition, the focus on identity and CMC addressed more specific literature than previous, broader reviews (e.g., Earl et al., 2014; Earl & Kimport, 2011). In this way, we contributed to multiple research fields by providing a research agenda on the interplay between identity, collection action and CMC to better understand the role of identity in collective action and the circumstances under which CMC influences identification processes. In addition, we showed our results' practical implications for the

organization of collective action to achieve social change in a society characterized by the pervasive influence of CMC.

Chapter 3

Exploring the Temporal Evolution of Communication Networks during a Social Movement Campaign on Twitter

This is a single-author chapter. Earlier versions of the chapter were presented at the *American Sociological Association Annual Meeting* in Philadelphia, US (Priante, 2018a) and the *XXXVIII Sunbelt Conference* in Utrecht, The Netherlands (Priante, 2018b).

Abstract

Although the study of communication networks in online collective action is popular in the field of network and social movement studies, little is known about the temporal evolution of online networks. Knowledge of what the relationship is between such networks and mobilization dynamics and outcomes, the diffusion of movements, and the emergence of collective identities is limited. By focusing on social movement campaigns on social media, I investigate how online communication networks generated by the movement members structurally and socially evolve over time and how such networks shape the movement's collective identity. In addition, I look at the role such network structures and the resulting collective identity play in achieving mobilization outcomes, such as fundraising for social causes. In this chapter, I adopt a network approach combining social network analysis and network visualizations to study online collective action. As an empirical context, I use the 2014 US Movember health campaign on Twitter organized by the Movember Foundation, a social movement organization that raises awareness of prostate and testicular cancer. I find that the campaign's communication network has a characteristic three-layer structure comprising (1) a network core surrounded by (2) a constellation of smaller groups and (3) a periphery of isolated nodes. Inside this structure, movement members mostly converse with each other instead of remaining isolated. Although the three-layer structure is maintained over time, its robustness fades. As the campaign unfolds, the communication network goes through a latency phase during which people decrease their active participation and move to the periphery of the communication or even leave the campaign network. Furthermore, I find that network structures shape the movement's collective identity, which appears as a connected but distributed entity. Its maintenance over time, however, is guaranteed only by a small number of highly committed members, who are also very engaged in collecting donations for the campaign cause. This study offers contributions to research on social networks, social movements, and communication. Practical implications for social movement organizations are also discussed.

3.1 Introduction

Social movement research has traditionally highlighted the role of social networks in the organization of collective action, such as advocacy campaigns and protests (e.g., Diani & Della Porta, 2006; Diani & McAdam, 2003; Gould, 1993; Marwell et al., 1988; McAdam, 1986; Snow et al., 1980). With the advent of the digital age, social media have provided new platforms for the coordination and mobilization of social movements (Bimber et al., 2012; Earl et al., 2014; Earl & Kimport, 2011), where communication processes become instrumental in organizing action (Bennett & Segerberg, 2012; Bimber et al., 2005; González-Bailón & Wang, 2016). For example, when people use Twitter in campaigns to promote health or in protests to achieve political change, they create relations with others by sending messages called *tweets*. In so doing, they generate communication networks (Freeman, 1979; Friedkin, 1991; Wasserman & Faust, 1994) that provide opportunity structures facilitating (or constraining) collective action (González-Bailón et al., 2013; González-Bailón & Wang, 2016).

Scholars have investigated the role of networks in online mobilization (for reviews, see Earl et al., 2014; Mattoni & Treré, 2014) and have produced a variety of research outcomes pertaining to the conditions under which online networks are decisive for mobilization (González-Bailón & Wang, 2016). However, research into such networks' temporal evolution and the socio-structural changes they undergo has been limited (for an exception, see Bastos & Mercea, 2016; Mattoni & Treré, 2014; Pavan, 2017). As social movements are dynamic processes (Della Porta & Diani, 2006; Melucci, 1995), investigating networks' evolution makes it possible to unravel the temporal trends that can explain mobilization dynamics, the diffusion of movements, and the emergence of collective identities (Barberá et al., 2015; González-Bailón & Wang, 2016; Mattoni & Treré, 2014; Pavan, 2017; Tindall, 2004).

By adopting a network approach to study collective action, I examine the evolution of online communication networks as the outcome of people's production of content during social movement campaigns. In particular, I look at the structural and social changes of such networks by adopting a temporal bracketing strategy approach (Langley, 2009) to identify and analyze various 'temporalities' (Mattoni & Treré, 2014, p. 256) in online campaigns. In addition, I examine how online campaign communication networks shape and sustain the movement's collective identity over time. In this way, I answer calls in the literature to investigate how collective identities develop and are maintained over time during online mobilization (for a review, see Chapter 2 of this dissertation). This chapter provides a starting point to reflect on networks and identity as dynamic, complementary micro-dynamics of individual mobilization (see Chapter 1 of this dissertation). The first two research questions of this chapter are:

Question 3.1: How do online communication networks (a) structurally and (b) socially evolve over time in social movement campaigns?

Question 3.2: How do online communication networks shape and sustain the collective identity of the movements over time?

Furthermore, I look at how online communication network structures and the resulting collective identity offer the means to achieve mobilization outcomes beyond the mere volume of communication produced during online campaigns. The empirical case used in this chapter is the Movember campaign to promote awareness of men's health and to collect donations for this cause (Movember, 2014). In this vein, this chapter also addresses the following research question:

Question 3.3: What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

By combining structural network analysis and network visualizations, I investigate the evolution of the communication network generated on Twitter by members of the Movember movement during the 2014 US campaign. Although the focus on a single case study might affect the generalizability of the research outcomes, the mechanisms at work in the Movember campaign's network and, more broadly, the Movember movement point to generic conditions able to provide important insights that could help to explain the temporal dynamics of many other networks.

This study offers contributions to research at the intersection of literatures dealing with social networks, social movements, and communication. By investigating the temporal evolution of communication networks, this chapter deepens our understanding of the role that online networks play in the growth of social movements and of how network structures and collective identities are dynamic and complementary dimensions of collective action in the digital age (see Chapter 2 of this dissertation).

The rest of the chapter is structured as follows. First, I outline the theoretical background to understand networks as communication structures for online mobilization and the importance of linking temporality, networks, collective identity, and mobilization outcomes (Section 3.2). Next, I present the case study, data and methods (Section 3.3), followed by the results (Section 3.4) and discussion (Section 3.5). Limitations and contributions are presented in the last part of the chapter (Section 3.6).

3.2 Theoretical background

The study of communication and networks has a longstanding tradition in social sciences and can be traced back to the work of Bavelas (1950), Bavelas et al. (1951), Leavitt (1951), Freeman (1979), and Freeman et al. (1980), among others. Human communication is seen as the result of interactions between individuals, and networks of relations form structures through which communication flows (Wasserman & Faust, 1994). In networks terms, any communication process can be seen as a *graph*: Individuals are *nodes*, and *edges* represent the exchange of information or messages in communication (Freeman, 1979; Friedkin, 1991; Wasserman & Faust, 1994).

The study of networks as communication structures has gained momentum in social movement research investigating networks as structuring processes for collective action in the digital age (see Bimber et al., 2012; González-Bailón et al., 2013; González-Bailón & Wang, 2016; Mattoni & Treré, 2014). Social media like Facebook and Twitter provide open platforms where people interact with each other via communication processes during protests or campaigns and generate online communication networks that can facilitate (or constrain) collective action (González-Bailón et al., 2013; González-Bailón & Wang, 2016). Thus, social media are considered tools that support network relationships and connections as informal preconditions for more centralized mobilization (Bimber et al., 2012; Diani, 2000, 2011; Earl & Kimport, 2011).

Scholars have investigated the role of online networks in social movements (for reviews, see Earl et al., 2014; Mattoni & Treré, 2014). They argue it is important to focus on the characteristics of such network structures and to study and distinguish between different types of (online) mobilization (Diani & McAdam, 2003; Tindall, 2004). From a structural point of view, scholars find that online communication networks generated during online protests or campaigns are very large in size because participation in collective action has become easier and faster with the emergence of social media as mobilization tools (e.g., Barberá et al., 2015; González-Bailón & Wang, 2016). Owing to their large size, online networks are generally very sparse and fragmented because of high levels of local clustering, where people engage in communication processes in and between small groups (González-Bailón et al., 2013; González-Bailón & Wang, 2016; Pavan, 2017). When mobilization is the result of a planned effort, as in the case with campaigns organized by social movement organizations, these networks tend to be highly centralized and have a “star-shape” (Diani & McAdam, 2003; Freeman et al., 1980), where the campaign organizer usually occupies the center of the network (Pavan, 2017). In other cases, high centralization is due to the presence of a small group of highly connected and committed (individual or organizational) actors (Barberá et al., 2015). These central actors are able to build bridges through disconnected networks and, thus, play a pivotal role in facilitating

(or constraining) the communication process that can guarantee successful mobilization (González-Bailón & Wang, 2016).

This variety of research outcomes shows that communication networks provide opportunity structures for mobilization and, more broadly, the development of social movements. However, research on online networks and social movements has often investigated networks as static, instant snapshots without unpacking the various “temporalities” in which mobilization unfolds (Mattoni & Treré, 2014, p. 256). Social movements are indeed acknowledged as dynamic processes that evolve over time and are the result of interactions among various actors (Della Porta & Diani, 2006; Melucci, 1995). Scholars argue that the study of the temporal evolution of online networks improves our understanding of the long-term implications of such networks for mobilization (Bastos & Mercea, 2016; González-Bailón & Wang, 2016; Mattoni & Treré, 2014; Pavan, 2017). Studying temporality in networks makes it possible to unpack the complex dynamics of communication strategies that are at work during mobilization.

Social media offer various ways for people to engage in communication. Twitter, for example, is largely studied as an ideal platform to investigate communication strategies (e.g., boyd, Golder, & Lotan, 2010; Bruns & Stieglitz, 2014), especially in mobilization contexts (Barberá et al., 2015; Bennett & Segerberg, 2012; González-Bailón & Wang, 2016; Pavan, 2017; Tremayne, 2014). On Twitter, tweets, mentions, replies, and retweets are messages involving registered users. Thus, tweets, mentions, replies, and retweets represent various social, communicative acts of people participating in the communication process. The use of tweets indicates the adoption of an annunciative approach because they are messages that product contents but do not address any particular other (Bruns & Stieglitz, 2014). Replies and mentions denote a conversational approach because they represent direct and interactive communication edges between users (Bruns & Stieglitz, 2014). The presence of retweets, by contrast, signals the adoption of a disseminative approach because retweets are copies of other tweets that, when rebroadcasted, reach a wider audience (Bruns & Stieglitz, 2014). Over time, these three communication strategies (annunciative, conversational, and disseminative) might change as the network structure evolves. For example, in a recent study about the transnational feminist campaign “Take Back The Tech!” on Twitter, Pavan (2017) finds that campaign participants adopt different communication strategies as the movement evolves. In another study about the use of Twitter during the Gezi Park demonstrations in Turkey, Varol et al. (2014) find that online network structures are increasingly characterized by the predominance of annunciative and disseminative strategies over time: In other words, as the protest unfolds, the production of content (tweets) and its rebroadcasting (retweets) increase and become more widely distributed among the protest participants.

Research into networks and social movements also investigates the role of online networks in shaping and sustaining a movement's collective identity (e.g., Ackland & O'Neil, 2011; Monterde et al., 2015; Vicari, 2014). Melucci defines collective identity as "a network of active relationships between the actors, who interact, communicate, influence each other, negotiate and make decisions" (Melucci, 1995, p. 45). A collective identity implies a certain degree of emotional investment (Melucci, 1995) and a sense of "we-ness" (Snow, 2001), which distinguishes the collective self from the "others" via the creation of active relationships. In other words, a collective identity defines the boundaries of the collective actor by regulating individuals' membership to the movement (Flesher Fominaya, 2010; Melucci, 1995). Collective identities are not static entities but rather dynamic processes emerging from the interactions of movement members who mobilize to achieve a common goal (Flesher Fominaya, 2010; Melucci, 1995). In this regard, networks can foster the formation and evolution of a common sense of unity, that is, a collective identity (Melucci, 1995; Snow, 2001). Scholars investigating collective action in the digital age find evidence that movements' collective identities emerge from network structures of online interactions between the various actors who are part of the movement (e.g., Ackland & O'Neil, 2011; Monterde et al., 2015; van den Broek, 2016). In this view, the study of collective identity is often approached in a systemic way, that is, communication networks are analyzed in the structural and systemic aspects shaping the collective identity of the movement (Monterde et al., 2015). For example, investigating the structural characteristics of the *giant component* (i.e., the fully connected group with the most nodes) can shed light on the "systemic unity" of the network: A strongly connected and cohesive giant component not only shows high network centralization but also suggests the presence of a subset of strongly connected actors who represent the *core* of the movement's collective identity (Monterde et al., 2015). Scholars find that online networks also contribute to the development of symbolic collective identification within social movements (Ackland & O'Neil, 2011; Vicari, 2014). Thus, communication networks become channels via which movements and their members create, promote, and negotiate symbolic identifiers that foster the construction of collective identities during campaigns or protests (e.g., Kavada, 2015; Penney, 2015; Treré, 2015). In addition, communication networks and collective identity provide movement members with opportunity structures (González-Bailón & Wang, 2016) and motivation (e.g., Melucci, 1995; Snow, 2001), respectively, that enhance individual and collective mobilization outcomes and go beyond the online discussion generated during the campaign, such as collecting donations for the movement's cause.

By drawing on prior research into networks and social movements, I posit that the investigation of online communication networks' evolution can shed light on mobilization

dynamics and outcomes, the diffusion of movements, and the emergence of collective identities. First, I explore how communication networks generated by movements' members during mobilization structurally change over time by looking at the macro-structural network features (RQ 3.1a). Next, I examine the communication strategies adopted by movement members to assess how communication networks socially evolve over time (RQ 3.1b). Finally, I investigate how network structures shape and sustain the movements' collective identity (RQ 3.2) and provide a starting point to reflect on the importance of an integrative approach of network and identity to study individual and collective mobilization outcomes that go beyond the volume of communication generated during the campaign (RQ 3.3).

3.3 Methods

3.3.1 Research setting: the case of the Movember Foundation and its men's health campaign on Twitter

The research setting of this study includes the case of the Movember Foundation and its campaign to raise awareness of men's health. In particular, I focus on the structure of the communication network generated on Twitter by the Movember movement members. Below, I will briefly elaborate on the reasons for choosing this case.

First, research investigating the role of online networks in social movements mostly focuses on protests and disruptive events, such as the Arab Spring revolution (e.g., Earl et al., 2014; Sadiki, 2015; Volpi & Jasper, 2018), the Occupy and Indignados movements (for some recent examples, Conover et al. 2013; Earl et al. 2014; Flesher Fominaya 2015; González-Bailón and Wang 2016; Purakayastha 2017; Theocharis et al. 2015; Tremayne 2014; Vie, Carter, and Meyr 2018). Research covering other forms of mobilization, such as advocacy campaigns, is scant. This is an important omission as it obscures the role of networks in the growth of movements aimed at social (rather than political) change. Movember, for instance, is a global grassroots movement that promotes men's health globally (Movember, 2014). It was started by the Movember Foundation, a non-profit organization founded in 2003 in Australia. Every year in November, the Movember Foundation organizes campaigns around the world to raise awareness of prostate and testicular cancer and to collect donations for medical research. The foundation uses symbols, such as the moustache, and poses challenges, such as doing sports every day for a month, to make people identify with the cause. The foundation also allows people to become official members via an online registration and to open a personal profile on the foundation's website. Being an official member and adopting the moustache symbolizes belonging to the movement and a marked sense of collective identity (Jacobson & Mascaro, 2016). Since 2003, the Movember movement has officially registered 4,746,905

members (*MoBros* and *MoSistas*), who have gone on to raise about 580 million Australian dollars (Movember, 2014). Thus, the Movember movement is a good example of the traditional collective action logic: Its campaign is the result of a planned effort and is built on the active contribution of the Movember Foundation members.

Second, the case of the Movember campaign suits the study of online networks because the Movember Foundation largely uses social media to promote its campaign, spread the message, and encourage people to share their fundraising activities and personal stories (Movember, 2014). With the advent of social media, the Movember movement has expanded exponentially to the point that the foundation officially describes it as a digital movement (Jacobson & Mascaro, 2016; Movember, 2014). With regard to all forms of social media, Twitter is largely used by the Movember Foundation and its members to organize, coordinate, and communicate about mobilization (Bravo & Hoffman-Goetz, 2015; Jacobson & Mascaro, 2016; Prasetyo, Hauff, Nguyen, van den Broek, & Hiemstra, 2015). In this chapter, I focus on the Twitter communication network generated by the official individual members of the Movember Foundation during the campaign. A study of this kind of networks makes it possible to investigate the evolution of network structures and to assess the individual and collective contribution of the movement members to the campaign cause.

Third, since 2003 the Movember Foundation has run several editions of the campaign by attracting increasing numbers of members and participants for more than 10 years. The Movember campaign and movement have also piqued the interest of academics from various domains, including philanthropy (Jacobson, 2010; Robert, 2013), the study of non-profit organizations (Neff & Moss, 2011), health (Bravo & Hoffman-Goetz, 2015; Wassersug, Oliffe, & Han, 2015), and communication and media (Jacobson & Mascaro, 2016; Nguyen, van den Broek, Hauff, Hiemstra, & Ehrenhard, 2015; Prasetyo et al., 2015). The recurrence of Movember campaigns over the years makes the Movember case a good example of a well-established and consolidated campaign. Thus, the Movember campaign provides a solid case to identify and unpack the various temporalities of the campaign network and assess its socio-structural changes over time (RQ 3.1), to investigate the formation and maintenance of the Movember movement's collective identity (RQ 3.2), and to explore individual and collective outcomes resulting from online mobilization (RQ 3.3).

3.3.2 Data and communication network construction

In this study, I focus on the communication network generated during the US Movember campaign on Twitter in November 2014. I chose the United States because the US campaign is one of the oldest and largest Movember campaigns and had some of the highest numbers of active members and participants over time (Movember, 2014). I used

the 2014 edition because this is when social media became a consolidated mobilization tool for the campaign (Movember, 2014). In this chapter, I regard the Movember campaign's communication network as the outcome of movement members' activity in generating content. Consequently, the population of this study covers those US Movember movement members ($N=3,295$) who were officially registered as official members (*MoBros* and *MoSistas*) and used Twitter during the 2014 campaign. The identification of the official members and access to their tweets was granted by a Twitter #datagrants project on large online cancer awareness campaigns (see Introduction, Section 1.5). From the dataset, I retrieved 14,970 tweets sent by the 3,295 officially registered members from 15 October 2014 to 15 December 2014¹¹. These tweets were used to build the communication network of the Movember campaign. Members are nodes, and the communicative relations derived from their Twitter activity are edges. The Twitter platform allows the use of four types of message features that can be translated into four types of network relations. A tweet is a message sent by user A without generating any interaction, thus resulting in an edge (self-loop) that starts from and ends with the same node ($A \rightarrow A$). Replies, mentions, and retweets, by contrast, represent communication edges, more specifically:

- a reply is user A's direct answer to user B's tweet ($A \rightarrow B$);
- a mention is a tweet by user A that explicitly refers to user B in order to alert him/her about something ($A \rightarrow B$); and
- a retweet is user A's copy and rebroadcasting of user B's tweet ($A \rightarrow B$).

To build the communication network, I developed a Python script¹² that turns mentions, replies, and retweets into directed edges linking the sender (A) with the recipient (B) of the message. Regular tweets, by contrast, are treated as self-loops. In this way, people sending only regular tweets are isolated nodes. Edges derived from tweets, mentions, replies, and retweets are also weighted as they might co-occur between two nodes (i.e., the weight of an edge is equal to the number of co-occurrences). As movement members might mention, reply to, or retweet other Twitter users' messages, additional nodes ($N = 3,309$) were automatically added to the 3,295 nodes representing the Movember movement members. These additional users were considered external targets (or audiences) of the movement members. Thus, the resulting Movember campaign network is a directed graph comprising 6,604 nodes and 8,863 (weighted) edges.

¹¹ More information on the Twitter data collection and preparation are provided in Appendix B at the end of this dissertation.

¹² The code related to this script is available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

Figure 3.1. Communication networks of the US Movember campaign on Twitter at each phase (I).

Black disks are nodes, whereas edges are colored according to the type of communication strategy: red for mentions, blue for retweets, and green for replies. Self-loops derived from regular tweets are identified by a thin, orange line around the node. The network visualizations were realized using Fruchterman Reingold, Force Atlas 2, and Yifan Hu Proportional algorithms in Gephi.

As I am interested in investigating the Movember network's evolution, I used short-term temporalities to divide the campaign's network into phases. I adopted the temporal bracketing strategy approach for process data¹³ to decompose chronological data into subsequent, comparable periods (Langley, 2009). The identification of the phases was guided by the analysis of patterns emerging from the Twitter activity and the identification of peaks and troughs of activity as “punctuated events” (Mattoni & Treré, 2014, p. 256). In this way, I obtained four campaign phases: the pre-campaign, or launching, phase from 15 to 31 October (T1); the campaign's first two weeks, from 1 to 15 November (T2); the

¹³ Details on the temporal bracketing procedure are provided in Appendix C.

campaign's second two weeks, from 16 to 30 November (T3); and the post-campaign phase, from 1 to 15 December (T4). Figure 3.1 shows the four communication networks (one for each of the campaign phases).

3.3.3 Analytical approach

I conducted a social network analysis using Gephi 0.9.2 (Bastian, Heymann, & Jacomy, 2009) to assess the network features of each campaign phase (T) and provide a descriptive analysis of the evolution of the network structure over time. First, I calculated the macro network features to assess the structural changes of the network (RQ 3.1a), such as network size, number of edges, network density (i.e., the proportion of the actual communication edges in the network and the total possible edges), and average weighted degree (i.e., the average of the number of edges for all nodes weighted by how many times a relation occurs) at each T. These measures are used to assess the network's size and level of sparseness. In addition, I used component analysis based on Tarjan's (1972) algorithm to detect the number of connected components of at least two nodes and, among them, to identify the giant component. These measures are used to assess the level of fragmentation and centralization of the online network.

Second, I focused on the communication strategies adopted by movement members to identify social changes in the communication networks (RQ 3.1b). In particular, I associated each type of relations existing among members on Twitter (i.e., tweet, mentions, replies, and retweets) with a specific communication approach. As in Bruns and Stieglitz (2014), the use of mentions and replies signals the presence of a "conversational approach," whereas the predominance of tweets stands for an "annunciative approach" and retweets for a "disseminative approach." Next, I looked at the distribution of types of relations over the campaign's phases to assess the social changes of the network in terms of how communication strategies varied over time.

Third, I focused on the giant component (i.e., the fully connected group with the most nodes) to describe how the network structure shapes and sustains the Movember movement's collective identity over time (RQ 3.2). In line with Monterde et al. (2015), I considered collective identity as the communication network's systemic unity and examined the internal, statistical configuration of the giant component. In particular, I used the Louvain modularity method (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) for community detection and k-core decomposition (Seidman, 1983) in the giant component. The Louvain modularity method is based on the concept of community (or module), which is a subset of nodes that are well connected inside the community but less with the outside (for a review of community detection, see Leskovec, Lang, and Mahoney 2010). The modularity algorithm measures internal connectivity with "reference to a

randomized null model” (Leskovec et al., 2010, p. 2), which means the algorithm generates different communities each time the algorithm is used. In other words, the Louvain modularity algorithm can detect an indeterminate number of communities inside a network. Consequently, a modularity resolution threshold has to be set in order to assess the level of internal connectivity detected by the algorithm (Blondel et al., 2008). In using Louvain modularity method, I followed the approach of Monterde et al. (2015, p. 937) by selecting a threshold parameter that is based on “optimization for stability” of flows within the community. The optimal parameter was 3, with modularity resolution values varying from 2.289 to 2.307 according to the campaign phase. Once the communities were identified, I looked at their internal, statistical configuration to assess the network characteristics of the collective identity, or systemic unity, of the movement over time. Next, k-core decomposition was used to determine whether the network’s systemic unity has a robust structure over time (Dorogovtsev, Goltsev, & Mendes, 2006; Seidman, 1983). The concept of k-core is based on the degree of a node. The degree of a node is the number of communicative connections that a node has with other nodes in the network. As the Movember campaign’s communication network is a directed graph made by in- and out-links, the degree of a node is calculated as the sum of in-degree and out-degree. By definition, k-cores are subsets of a network obtained by a recursive approach that, from the whole network, progressively removes nodes of degree less than k (Alvarez-Hamelin et al. 2006). In other words, k-cores are groups of nodes whose cohesion increases as the degree k increases (Seidman 1983). Consequently, nodes with the highest value of k represent the most cohesive subgroup of the network. I used k-core decomposition on the giant component to detect its core as the most cohesive group of nodes and to determine the level of robustness of its structure.

Last, I shifted the focus to an analysis of individual and collective mobilization outcomes that were beyond the volume of online communication (i.e., Twitter activity) generated during the campaign (RQ 3.3). In particular, I looked at individual and collective fundraising outcomes reached by movement members via their Twitter activity during the four phases of the Movember campaign. I obtained members’ donation data (i.e., individual amount of US dollar donations per day) from the US Movember Foundation. To answer RQ 3.3, I aggregated the donation data at both the individual and the collective level by calculating the average and total amount of donations at each phase of the campaign. I then interpreted the results on the basis of the communication network structure and the characteristics of the collective identity.

3.4 Results

3.4.1 Structural and social evolution of the Movember campaign communication network

Table 3.1 shows the macro network features at each campaign phase to assess the structural evolution of the Movember campaign communication network’s structural changes over time (RQ 3.1a).

Table 3.1. Macro network features at each phase (I) of the Movember campaign.

	Phases			
	T1	T2	T3	T4
	<i>Pre-campaign</i>	<i>First two campaign weeks</i>	<i>Second two campaign weeks</i>	<i>Post-campaign</i>
Network size (number of nodes)	1,437	4,525	2,737	768
<i>Isolates (%)</i>	20.04%	22.87%	24.88%	28.26%
<i>In the giant component (%)</i>	61.93%	62.54%	50.71%	27.08%
<i>In smaller components (%)</i>	18.03%	14.59%	24.41%	44.66%
Number of edges	2,431	9,625	5,589	972
<i>Weighted (sum)</i>	1,666	5,637	3,208	745
<i>Interactive vs. self-loops (%)</i>	72.45%	66.9%	65.4%	60.94%
<i>Unimodal vs. bimodal (%)</i>	77.91%	71.67%	72.19%	83.22%
Density	0.001	0.000	0.000	0.002
Average (mean) weighted degree	1.135	1.177	1.161	0.767
<i>Max weighted degree</i>	586	2,248	1,037	145
Connected components (of at least two nodes)	90	225	225	130

Source: Twitter data obtained via a Twitter datagrant on large online cancer awareness campaigns.

The network size indicates that the network was at its largest during the first two campaign weeks (T2), after which the number of nodes decreased by half (T3). Not surprisingly, the post-campaign phase (T4) is the smallest one and shows a decrease of participation after the formal end of the campaign (30 November). The Movember communication network is invariably very sparse over time: Network density is constantly very low, as is typical of large, online networks. The sparseness notwithstanding, the disproportion between the average weighted degree and the highest degree show the presence of a small group of central users with a much higher degree than in all the other nodes. Among them, the official Twitter account of the Movember Foundation has the highest (in)degree value over time, as it is the most frequent target of movement members’ mentions, replies, and retweets. This pattern not only shows the typical power-law distribution of large networks (Barash, Cameron, & Macy, 2012; Litvak, 2018) but also suggests the presence of a centralized network structure that is maintained over time.

The analysis of the structural components provides additional details about the network structure of the Movember campaign (RQ 3.1a). As Table 3.1 shows, the communication

network is characterized by large numbers of strongly connected components, that is, groups of nodes where any two vertices are connected to each other by paths. In other words, the communication network is fragmented and nested in groups. As Figure 3.1 shows, the campaign network is characterized by a three-layer structure comprising (1) a core of strongly connected movement members surrounded by (2) a constellation of smaller groups and (3) a periphery of isolated nodes that are not involved in any communicative interactions. The innermost layer, or core, is the strongly connected giant component, that is, the group with the most nodes connected with each other. Outside the giant component, communication is fragmented and locally clustered into several small groups (mostly dyads and triads) where nodes are involved in a communication exchange with a few other nodes. The third, more external layer, instead, is made by all isolated movement members who do not interact with any others in the communication as they only send regular tweets (self-loops). This external area can be defined as the far periphery of the network.

Although this three-layer structure is maintained over time, as shown in Figure 3.1, the robustness of such structure decreases as the campaign unfolds. As Table 3.1 shows, the size of the giant component gradually decreases. The launching phase (T1) and the first two weeks of the campaign (T2) are the ones with the largest core of strongly connected nodes. In T3 and T4, nodes move toward more peripheral, fragmented, and disconnected areas of the network or even exit the network, as shown by the decrease of the network size starting from the second two campaign's weeks. After the formal end of the campaign (T4), the giant component is reduced to a quarter of the total number of nodes, and online communication is highly nested in small groups. Altogether, these findings show that the Movember campaign's communication network has a characteristic structure that, although it maintains a three-layer configuration, changes over time in terms of its robustness.

Next, I look at the social changes of the network structure as the result of users' generation of contents (RQ 3.1b). Inside this structure, communication flows between movement members via at least one interaction, as shown by the values of the average weighted degree and the predominance of interactive edges. In other words, movement members interact with each other to a certain extent. The distribution of communicative edges derived from tweets, replies, mentions, and retweets indicates the presence of distinct communication strategies, which shows a minimum degree of interaction. As Figure 3.2 demonstrates, movement members mostly adopt a conversational approach (i.e., they interact with others via mentions or replies) over time rather than remaining isolated by adopting an annunciative approach (i.e., they send only regular tweets). This shows that the campaign communication network does not socially change over time but, instead, remains intact as movement members consistently adopt conversational

Figure 3.2. Movember members’ communicative approach at each phase (T) of the Movember campaign. The approach is determined by the volume of communication ties derived from Twitter activity: annunciative (from tweets), conversational (from replies and mentions), and disseminative (from retweets).

communication strategies over time. In spite of the predominance of the conversational approach, as the campaign unfolds, the communication network becomes less interactive, as shown by the increasing number of isolated nodes over time. In addition, communicative ties are mostly unimodal, that is, movement members do interact with each other but rarely more than once. Thus, the communication exchange is “flat” because communication processes are simple and guaranteed by the basic interactions occurring on the Twitter platform.

3.4.2 Communication networks and collective identity over time

In this chapter, I approach the study of the Movember campaign’s collective identity in a systemic way. I assess the collective identity as the systemic unity of the campaign communication network. I examine the giant component’s internal, statistical configuration in order to determine how network structures shape and sustain the collective identity of the movement over time (RQ 3.2). I used Louvain’s community detection analysis (Blondel et al., 2008) and k-core decomposition (Dorogovtsev et al., 2006; Seidman, 1983) to assess whether such a collective identity exhibits a (robust) centralized or decentralized structure. Outcomes from the community detection analysis and the k-core decomposition are presented in Table 3.2, whereas visualizations of the resulting networks are plotted in Panel 3.1. In interpreting the results, I also look at how the official Movember members are distributed over time in the three-layer network

structure to assess whether movement members play a substantial role in shaping and maintaining the collective identity over time (Table 3.3).

As mentioned in the previous section, the size of the giant component gradually decreases, in particular during the third week of the campaign. Although movement members’ participation in the online communication network decreases by half between T2 (84.2%) and T3 (47.0%), as shown in Table 3.3, a substantial portion of MoBros and MoSistas (39.77%) is still located in the giant component in the second two weeks of the campaign, which shows that the systemic unity, or identity, of the movement is maintained over time by a small number of members. After the formal end of the campaign, only 14% of the members are active on Twitter and, among them, 23.24% are located in the giant component.

With regard to the internal configuration of the giant component, various statistical properties describe the systemic unity of the network. The Louvain algorithm, when applied to the giant component, detects several communities of nodes that are well connected on the inside but less connected with the outside of the community (Table 3.2). Although the presence of several communities suggests high levels of fragmentation inside the giant component over time, the biggest of these communities contains the majority of nodes of the giant component. In other words, the collective identity is fragmented into groups that are all connected.

Table 3.2. Assessing the collective identity of the Movember campaign as the network’s systemic unity: Community detection analysis and *k*-core decomposition inside the giant component at each phase (I).

	Phases			
	T1	T2	T3	T4
	<i>Pre-campaign</i>	<i>First two campaign weeks</i>	<i>Second two campaign weeks</i>	<i>Post-campaign</i>
<u>Community detection</u>				
Detected communities	17	101	41	12
Big communities (% of visible nodes > 1)	5	5	7	4
<i>Nodes (as a percentage of the size of the giant component)</i>	97%	76%	81%	81%
<i>Avg. (weighted) degree</i>	1.614	1.736	1.939	1.706
<i>Avg. clustering coefficient</i>	10.4	4.3	32.3	17.5
<u>K-core decomposition</u>				
Max <i>k</i> -core				2
<i>% of visible nodes and edges in max k-core</i>	3	4	4	5,21%;
	2,85%; 7,95%	1,41%; 4,96%	0,58%; 1,95%	14,32%

Source: Twitter data obtained via a Twitter datagrant on large online cancer awareness campaigns.

Table 3.3. Distributions of official Movember members (% of nodes) per network layer over time.

	Phases			
	T1	T2	T3	T4
	<i>Pre-campaign</i>	<i>First two campaign weeks</i>	<i>Second two campaign weeks</i>	<i>Post-campaign</i>
Number of members	786	2,772	1,549	462
(percentage compared to the total number of members)	23.85%	84.1%	47.0%	14.0%
Located in:				
<i>Giant component</i>	50.89%	53.43%	39.77%	23.24%
<i>Smaller communities</i>	12.47%	9.24%	16.27%	26.76%
<i>Isolates</i>	36.64%	37.34%	43.96%	50.00%

Source: Twitter data obtained via a Twitter datagram on large online cancer awareness campaigns.

Figures 1a, 2a, 3a, and 4a in Panel 3.1 plot the biggest communities inside the giant component and show how the network’s systemic unity builds up a characteristic snowflake configuration over time. The giant component is centered in one large community (C1, C6, C11, and C18, respectively, for each phase), where the Twitter official account of the US Movember Foundation occupies the center (green node). Most of the official members, identified by red nodes, are concentrated inside this big community. However, they form part of such a community because they are mostly connected to the Movember Foundation’s account rather than with each other. At each time T, several smaller clusters depart from the big community centered in the Movember official account, depicting a structure resembling a snowflake. The big community is the center, or nucleus, and the smaller communities are arms. Each “arm” of the snowflake grows independently from the center, while still being connected to it. Then, either side of each arm might grow on its own. As snowflakes are rarely regular in shape, such variety is visible in the configuration of these communities departing from the biggest one. Some of these smaller clusters (e.g., C3, C4, C19, C20, and C21) – especially in T1 and T4 – present a typical star-shape structure where the center is occupied by an official member who creates communicative relations with their audiences (green nodes). By contrast, other communities (e.g., C2, C7, and C8) present a decentralized and distributed structure, in particular during the first weeks of the campaign (T2). Inside these communities, various official members (red nodes) engage in communicative interactions – mostly with each other instead of their local audiences (green nodes), as shown by the percentages reported in Panel 3.1. Therefore, in identity terms, the collective identity emerging from the campaign network appears as a connected but distributed entity, where the unity is guaranteed by the central position of the Movember organization and a subset of movement members that decreases over time.

Panel 3.1. Modularity and k -core decomposition in the giant component at each phase (T) of the November campaign. Figures 1a, 2a, 3a, and 4a show the biggest communities (i.e., percentage of visible nodes > 1) in the giant component after Louvain community detection. Different colors are assigned to nodes according to whether (red) or not (green) they are official members. Percentages of distribution of members and their audience are also reported. *Continued.*

Continued. Figures 1b, 2b, 3b, and 4b show the maximal cohesive subgraph (i.e., all the nodes have the same degree) in the giant component after the k-core decomposition. These visualizations were produced using Force Atlas 2 and Yu Han Proportional algorithms in Gephi.

Although the snowflake configuration is recognizable in each phase of the campaign's network (Panel 3.1), its internal characteristics (connectedness and cohesion) vary over time. On the one hand, connectedness is important to shape the collective identity as it makes it a systemic unity. It is measured by the average weighed degree as the average number of connections of nodes in the communities: The higher the value, the more the systemic unity of the network is formed by connected nodes (Monterde et al., 2015). On the other hand, cohesion is a fundamental aspect not only to form but also to maintain a collective identity (Flesher Fominaya, 2015; Monterde et al., 2015; Moody & White, 2003; Thomas, McGarty, & Mavor, 2009; Treré, 2015; Vicari, 2014). The average clustering coefficient informs about how much nodes are embedded in their communities at T: The higher the value, the more the systemic unity of the network, or identity, is made by cohesive nodes. Table 3.2 reports the values of average weighed degree and average clustering coefficient at each T. While in the first two campaign weeks the systemic unity is shaped by a large number of loosely connected and less embedded nodes, as the campaign unfolds only a small but more cohesive and connected group of nodes sustain the systemic unity of the network.

Results from the k-core decomposition provide further validation of this finding as it informs about the level of the robustness of the network's systemic unity (Monterde et al. 2015, Seidman 1983). Figures 1b, 2b, 3b, and 4b in Panel 3.1 show the k-core decomposition of the giant component to the largest k value before the network completely disappears. The resulting set of nodes represent the very core of the campaign's network as the most cohesive subgroup in the giant component. As the figures in Panel 3.1 and Table 3.2 show, the network's most cohesive core is very small in size, in particular during the four campaign weeks and especially in T3, where the percentages of visible edges and nodes are very small. At the structural level, as shown in Figures 1b, 2b, 3b, and 4b, the most cohesive group only vaguely approaches the complete structure of the giant component, in particular in T1 and T2. In these phases, the network core is reduced to a few members connected to the Movember Foundation's Twitter account. This shows that, although the giant component is bigger in these phases than later, its internal structure lacks cohesion. As the campaign unfolds and in movement members move to the periphery of the network (as shown in Table 3.1 and Table 3.3), the giant component and its core become smaller but more robust in structure. As Figures 3b and 4b show, the community's initial configuration is somewhat maintained and the level of average local clustering in these two phases is higher than in T1 and T2, which points to greater internal cohesion. Taken together, these findings show that network structures shape the movement's collective identity, which appears as a connected but distributed entity. Its maintenance over time, however, is guaranteed only by a small number of highly committed members.

3.4.3 What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

Having established the structural and social evolution of the Movember communication network (RQ 3.1) and how it shapes and maintains collective identity over time (RQ 3.2), I now turn to the third and final research question of this chapter (RQ3.3): What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

Table 3.4 shows the total and average amount of donations collected over time by members in each layer of the communication network. The total amount provides information about the collective effort of movement members, whereas the mean value offers insight as to how much the average member contributed to the cause (individual effort). Not surprisingly, at the collective level, the highest total amount of donations is collected during the first two campaign weeks (T1), which is the phase with the highest participation rate. In addition, people located in the giant component also collectively raise more donations over time than members located in other layers. However, the average amount of collected donations shows that in the latency phase (T3) people collect more money per person than before. This case applies not only to members of the giant component but also to the other layers. Although there are fewer members inside the network and the collective identity of the movement is sustained by only a few of them (as shown above in section 3.4.2), these members are more successful on average in their fundraising activities, and even more after the end of the campaign. In other words, the pre-campaign phase and the first two weeks collectively have a greater impact in terms of online participation and offline outcomes, such as donations raised. As the campaign enters its latency phase, fewer members participate in the campaign, but their individual effort and contributions to the campaign's cause are bigger than in the previous phases.

Table 3.4. Average and total amount of donations (in US dollars and percentage) collected by official members per network layer at each phase (I) of the November campaign. For comparison, the average and total amount of donations collected by official members outside the network at each 'T', as well as the final total amount collected at each 'T', are also reported.

	Phases									
	T1			T2			T3			T4
	<i>Pre-campaign</i>			<i>First two campaign weeks</i>			<i>Second two campaign weeks</i>			<i>Post-campaign</i>
	Avg. (\$)	TOT (\$)	%	Avg. (\$)	TOT (\$)	%	Avg. (\$)	TOT (\$)	%	TOT (\$)
Grant component	47.6	19,029.3	63.6	160.6	237,866.3	57.1	300.3	185,009.8	55.2	405.2
Smaller communities	12.4	1,218.1	4.1	202.9	51,935.8	12.5	207.0	52,169.7	15.6	89.7
Isolates	33.5	9,659.7	32.3	122.5	126,779.3	30.4	144.0	98,081.0	29.3	151.8
TOT (inside)	38.0	29,907.1	64.9	150.3	416,581.4	91.2	216.4	335,260.4	74.6	194.1
TOT (outside)	6.5	16,202.7	35.1	76.7	40,117.0	8.8	65.4	114,165.8	25.4	31.0
TOT (final)		46,109.8	4.1		456,698.4	40.7		449,426.1	40.0	170,378.7

Source: November data provided by the US Member Foundation.

3.5 Discussion

Using the Movember men's health campaign on Twitter as an empirical case, this chapter answers the following research questions:

Question 3.1: How do online communication networks (a) structurally and (b) socially evolve over time in social movement campaigns?

Question 3.2: How do online communication networks shape and sustain the collective identity of the movements over time?

Question 3.3: What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

First, I found that, on the whole, the communication network of the Movember campaign is sparse, fragmented, and centralized in the official Twitter account of the Movember Foundation. The communication process is simple and guaranteed by (mostly) unimodal interactions across movements members, who predominantly adopt a conversational strategy (i.e., they mention or reply to others) when engaging in conversations with each other and their audiences. In terms of social changes (RQ 3.1b), this shows that the conversational approach remains predominant over time. Thus, I can conclude that Movember members utilize the Twitter platform to engage in communicative interactions with others. This translates into communication networks that tend to remain socially intact. This is a new result if compared with previous research focusing on health advocacy campaigns (e.g., Movember) that are found not to generate much conversation (e.g., Bravo and Hoffman-Goetz 2015, Jacobson and Mascaro 2016). Looking at how the network structurally evolves over time (RQ 3.1a), I found that the online communication network during the Movember campaign has a three-layer structure that is clearly recognizable in every phase of the campaign. This is in line with previous studies that find that macro network structures are usually maintained over time (e.g., Pavan 2017). Although this three-layer structure is maintained, its robustness decreases over time. As the campaign unfolds, people move to the periphery of the communication, where they engage in small groups interactions or even exit the campaign network. Thus, the study of short temporalities reveals that certain campaign phases might represent "stages of latency" in which people decrease their active participation. The second two campaign weeks (T3) represent a moment of latency in the Movember campaign. Fewer people participate in online discussion, as shown by the decrease in network size compared with the first two weeks. In addition, the communication network in this latency phase is particularly static, fragmented, and less interactive than during the launching phase and the

first campaign weeks. A possible explanation for this result could be the difficulty of keeping people engaged in the campaign for a long period of time. Four weeks of campaigning might be too lengthy a time period to keep members engaged in actively producing content. Thus, the question is whether it is effective for social movements, such as Movember, to organize such long campaigns.

Second, I looked at how the Movember campaign communication network shapes and sustains the movement's collective identity over time (RQ 3.2). In this chapter, I defined collective identity as the systemic unity of the network, that is, as the result of interactions occurring in the giant component of the network. I found that, although the giant component appears as a centralized structure, the campaign's systemic unity is guaranteed by the central Twitter account of the Movember Foundation and is distributed among various movement members, who contribute to building the network as a whole. However, owing to changes in network communicative interactions between movement members, the systemic collective identity's robustness varies over time. On the one hand, the first two campaign weeks (T2) are characterized by massive participation, which shapes the collective identity of the movement as a loosely cohesive and poorly interconnected structure. On the other hand, as the campaign unfolds in the second half of November (T3), the movement members move outside the giant component and prefer to engage in local interactions with small audiences, or even remain isolated, incapable of generating any communication process. Members located in the giant component, instead, become more connected and sustain the movement's collective identity that, although it is losing participants, becomes more internally cohesive. Cohesion is an important element to maintain a collective identity (Flesher Fominaya, 2015; Monterde et al., 2015; Moody & White, 2003; Thomas et al., 2009; Treré, 2015; Vicari, 2014) and seems to play a pivotal role in sustaining the network's unity over time, in particular during moments of latency. This systemic identity "shift" occurring during the campaign month might be a consequence of the campaign's long time span, during which it is hard not only to keep people engaged but also to sustain their collective identification as movement members, at least online. Official members play a major role in setting up the communication network, but only a few of them shape and sustain the movement's systemic, collective identity over time. These results show the importance of adopting an integrative approach combining the study of networks and identity to understand dynamics at play during online mobilization (Chapter 2 of this dissertation), where network structures and identification processes represent complementary dimensions in collective action.

Last, I focused on fundraising activity during the Movember campaign as mobilization outcomes that are beyond the volume of online communication (RQ 3.3). In fact, the Movember Foundation exploits social media to both promote conversation on men's health and collect donations for medical research into prostate and testicular cancer. By

looking at the individual and collective distribution of donations raised during the campaign, I found that the pre-campaign phase and the first two weeks have collectively more impact in terms of online participation and donations outcomes. As the campaign enters its latency phase, fewer members keep the campaign going, but their individual effort and contributions are bigger than during the previous phases. Although further statistical testing is needed to validate this descriptive evidence, this result opens venues for future research to investigate the individual versus collective dynamics at play in online collective action. In addition, differences in collected donations across different network layers suggest the need to investigate further whether holding particular structural positions in the communication network over time lead to more or less success in fundraising (see Chapter 5 of this dissertation). In this vein, a broader issue to address is the extent to which the temporal dynamics of online communication networks directly explain mobilization outcomes other than the diffusion of movements and the emergence of a collective identity. In the case of the Movember campaign, quite a significant amount of money was raised in the very far periphery of the network by isolated members and by members who did not always participate in the online communication process (as shown at the bottom of Table 3.4). This result might be explained by several factors. For example, Movember members might use Twitter merely to set up the campaign and spread the message before they move to other social media or online tactics or go offline. Or they might be good communicators and produce content or *frames* (Benford & Snow, 2000; Goffman, 1974) that motivate people to join the cause. Or they simply have money or friends with money. And so on. A great deal of prior research has investigated the conditions that make networks conducive to mobilization (González-Bailón & Wang, 2016). I argue that we should move empirical research to the next level in order to understand the extent to which network conditions can directly explain success in mobilization or, by contrast, act *in concert* with other (non-network) conditions.

3.6 Limitations and contributions

This study presents three limitations. First, owing to the focus on the Movember campaign on Twitter, this study's generalizability might suffer selection bias, which is a typical issue identified in studies of social movements and online networks (e.g., Lewis et al. 2014). However, the identified mechanisms that are in play relate to generic principles proper to many other networks. In this light, future research could use other types of advocacy campaigns and social media platforms to determine whether the network's structural and social changes found in this chapter can be confirmed in other settings.

Second, the use of temporal bracketing to identify campaign phases results in moderate generality and accuracy as this bracketing process is derived inductively and depends on the appropriateness of the temporal decomposition (Langley 1999, Langley 2009). Future studies could use additional data from other campaigns similar to Movember (e.g., Pink Ribbon) for replicative analysis. In the same vein, although this study investigates campaign temporalities, it does not consider the evolution of a campaign over the years. Future research should investigate whether the structural and social network changes highlighted in this chapter are the same in consecutive editions of the campaign.

Third, this chapter only looks at the macro dynamics of the network's temporal evolution. Only a little attention was devoted to micro-level aspects, such as movement members' structural position in the communication network. Future studies could focus on other individual dynamics, such as power and network roles, to assess whether mechanisms at the micro-level can explain macro network evolution, and who the pivotal actors responsible for such changes are. Additionally, investigating the content of what these actors share in online communication networks would shed light on the way in which they frame the discourse around the movement's collective identity.

Despite its limitations, this study offers four contributions. First, it answers the call for more longitudinal, temporal analysis of networks' effects on online collective action (Bastos and Mercea 2016, González-Bailón and Wang 2016, Mattoni and Treré 2014, Pavan 2017). This chapter investigates how online communication networks unfold over time by identifying and analyzing different 'temporalities' (Mattoni and Treré 2014) in online campaigns. This temporal analysis unravels both the structural and social changes of networks over time that characterize patterns of diffusion of movements, the emergence of collective identities, and individual and collective mobilization outcomes.

Second, this study answers the call for the adoption of an integrative approach that combines the study of networks and identity to deepen our understanding of collective action in the digital age (Chapter 2 of this dissertation). By exploring the relations between network structures and systemic and symbolic identification processes, this chapter provides a starting point to reflect on networks and identity as dynamic, complementary micro-dynamics of individual mobilization (see Chapter 1 and Chapter 2 of this dissertation).

Third, this study contributes to social movement theory by building on network and media literature to understand the role of online networks as an opportunity structure for collective action (e.g., González-Bailón et al., 2013; González-Bailón & Wang, 2016; Hara & Huang, 2011; van den Broek, Need, Ehrenhard, Priante, & Hiemstra, 2018). This chapter shows how Twitter can foster interactive communication network processes that are important for the development of online campaigns, movements, and identities. In this way, this chapter improves our understanding of the role of networks in social movements

using communication technologies (Barberá et al., 2015; González-Bailón & Wang, 2016; Lewis et al., 2014)

Fourth, this study uses complete Twitter data from officially registered movement members to track network communication processes and outcomes during large-scale advocacy campaigns over time (van Leeuwen & Wiepking, 2013). Most previous research either focuses on small portions of the network or creates communication networks from selected types of relational ties (e.g., networks were derived from mention or retweets). By considering the complete Twitter data of officially registered members belonging to the US Movember campaign in 2014, this study minimizes the sampling biases due to smaller samples and provides insight into the overall structure of online networks (González-Bailón, Wang, Rivero, Borge-Holthoefer, & Moreno, 2014).

In practical terms, this work can provide social movement organizations such as Movember with valuable insights into the effective organization of online advocacy campaigns. More specifically, social movement organizations get an important understanding of the network's structural and social mechanisms underlying the use of Twitter as a mobilization and communication tool in collective action.

Chapter 4

#WhoAmI in 160 Characters? Classifying Social Identities Based on Twitter Profile Descriptions

This chapter is based on Priante, A., Hiemstra, D., van den Broek, T., Saaed, A., Ehrenhard, M. L. and Need, A. (2016). #WhoAmI in 160 Characters? Classifying Social Identities Based on Twitter Profile Descriptions. In *Proceedings of 2016 EMNLP Workshop on Natural Language Processing and Computational Social Science* (pp. 55–65). Austin, TX, US.

Abstract

We combine social theory and natural language processing (NLP) methods to classify English-speaking Twitter users' online social identity in profile descriptions. We conduct two text classification experiments. In Experiment 1, we use a five-category online social identity classification based on identity and self-categorization theories. While we are able to automatically classify two identity categories (relational and occupational), automatic classification of the other three identities (political, ethnic/religious and stigmatized) is challenging. In Experiment 2, we test a combination of such identities (collective action-oriented identity) based on theoretical arguments. We find that by combining these identities we can improve the predictive performance of the classifiers in the experiment. Our study shows how social theory can be used to guide NLP methods, and how such methods provide input to revisit traditional social theory that is strongly consolidated in offline settings.

4.1 Introduction

Social movement organizations increasingly use social media, such as Twitter, to mobilize people and organize cause-related collective action, such as health advocacy campaigns. Studies in social psychology (Alberici & Milesi, 2013; Chan, 2014; Park & Yang, 2012; Postmes & Brunsting, 2002; Thomas et al., 2015; van Zomeren et al., 2008) demonstrate that social identity motivates people to participate in collective action, which is the joint pursuit of a common goal or interest (Olson, 1968). Social identity is an individual's self-concept derived from social roles or memberships to social groups (Stryker, 1980; Stryker et al., 2000; Tajfel, 1981; Turner et al., 1987). The use of language is strongly associated with an individual's social identity (Bucholtz & Hall, 2005; Nguyen et al., 2014; Tamburrini, Cinnirella, Jansen, & Bryden, 2015). On Twitter, profile descriptions and tweets are online expressions of people's identities. Therefore, social media provide an enormous amount of data for social scientists interested in studying how identities are expressed online via language.

We identify two main research opportunities for online identity. First, online identity research is often confined to relatively small datasets. Social scientists rarely exploit computational methods to measure identity over social media. Such methods may offer tools to enrich online identity research. For example, natural language processing (NLP) and machine learning (ML) methods assist to quickly classify and infer vast amounts of data. Various studies investigate how to predict individual characteristics from language use on Twitter, such as age and gender (Al Zamal, Liu, & Ruths, 2012; Burger, Henderson, Kim, & Zarrella, 2011; Ciot, Sonderegger, & Ruths, 2013; Nguyen, Gravel, Trieschnigg, & Meder, 2013; Nguyen et al., 2014; Preoțiuc-Pietro, Volkova, Lampos, Bachrach, & Aletras, 2015; Van Durme, 2012), personality and emotions (Preoțiuc-Pietro et al., 2015; Volkova & Bachrach, 2015; Volkova, Bachrach, Armstrong, & Sharma, 2015), political orientation and ethnicity (Al Zamal et al., 2012; Cohen & Ruths, 2013; Pennacchiotti & Popescu, 2011; Volkova, Coppersmith, & Van Durme, 2014), profession and interests (Al Zamal et al., 2012; Li, Ritter, & Hovy, 2014).

Second, only a few studies combine social theory and NLP methods to study online identity in relation to collective action. One recent example uses the Social Identity Model of Collective Action (van Zomeren et al., 2008) to study health campaigns organized on Twitter (Nguyen et al., 2015). The authors automatically identify participants' motivations to take action online by analyzing profile descriptions and tweets.

In this vein, our study contributes to scale-up research on online identity. The research question of this chapter is:

Question 4: To what extent can the social identity of Twitter users be predicted based on their profile description?

We explore automatic text classification of online identities based on a five-category social identity classification built on theories of identity. We analyze 2,633 English-speaking Twitter users' 160-characters profile description to classify their social identities. We only focus on profile descriptions as they represent the most immediate, essential expression of an individual's identity.

We conduct two classification experiments: Experiment 1 is based on the original five-category social identity classification, whereas Experiment 2 tests a combination of three categories for which automatic classification does not work in Experiment 1. We show that by combining these identities we can improve the predictive performance of the classifiers in the experiment.

Our study makes two main contributions. First, we combine social identity theory, natural language processing, and machine learning to classify English-speaking Twitter users' social identity on the basis of how they describe themselves in their profile description. We show how social theory can be used to guide NLP methods, and how such methods provide input to revisit traditional social theory that is strongly consolidated in offline settings.

Second, we evaluate different classification algorithms in the task of automatically classifying online social identities. We show that computers can perform a reliable automatic classification for most social identity categories. In this way, we provide social scientists with new tools (i.e., social identity classifiers) to scale up online identity research to massive datasets derived from social media.

The rest of the chapter is structured as follows. First, we illustrate the theoretical framework and the online social identity classification, which guides the text classification experiments (Section 4.2). Second, we explain the data collection (Section 4.3) and methods (Section 4.4). Third, we report the results of the two experiments (Section 4.5 and 4.6). Finally, we discuss our findings and provide recommendations for future research (Section 4.7).

4.2 Theoretical framework: a five-category online social identity classification grounded in social theory

We define social identity as an individual's self-definition based on social roles played in society or memberships of social groups. This definition combines two main theories in social psychology: identity theory (Stryker, 1980; Stryker et al., 2000) and social identity, or self-categorization, theory (Tajfel, 1981; Turner et al., 1987), which respectively focus

on social roles and memberships of social groups. We combine these two theories as together they provide a more complete definition of identity (Stets & Burke, 2000). The likelihood of participating in collective action does increase when individuals both identify themselves with a social group and are committed to the role(s) they play in the group (Stets & Burke, 2000).

We create a five-category online social identity classification that is based on previous studies of offline settings (Ashforth, Harrison, & Corley, 2008; Ashforth, Schinoff, & Rogers, 2016; Deaux, Reid, Mizrahi, & Ethier, 1995). We apply such classification to Twitter users' profile descriptions as they represent the most immediate, essential expression of an individual's identity (Jensen & Bang, 2013). While tweets mostly feature statements and conversations, the profile description provides a dedicated, limited (160 characters) space where users can write about their self-definitions they want to communicate on Twitter.

The five social identity categories of our classification are:

1. Relational identity: a self-definition based on (reciprocal or nonreciprocal) relationships that an individual has with other people, and on social roles played by the individual in society. Examples on Twitter are *"I am the father of an amazing baby girl!"*, *"Happily married to @John"*, *"Crazy Justin Bieber fan"*, *"Manchester United team is my family"*.
2. Occupational identity: a self-definition based on occupation, profession and career, individual vocations, avocations, interests and hobbies. Examples on Twitter are *"Manager Communication expert"*, *"I am a Gamer, YouTuber"*, *"Big fan of pizza!"*, *"Writing about my passions: love cooking traveling reading"*.
3. Political identity: a self-definition based on political affiliations, parties and groups, as well as being a member of social movements or taking part in collective action. Examples on Twitter are *"Feminist Activist"*, *"I am Democrat"*, *"I'm a council candidate in local elections for [...]"*, *"mobro in #movember"*, *"#BlackLivesMatter"*.
4. Ethnic/religious identity: a self-definition based on membership of ethnic or religious groups. Examples on Twitter are *"God first"*, *"Will also tweet about #atheism"*, *"Native Washingtonian"*, *"Scottish no Australian no-both?"*.
5. Stigmatized identity: a self-definition based on membership of a stigmatized group, which is considered different from what the society defines as normal according to social and cultural norms (Goffman, 1959). Examples on Twitter are *"People call me an affectionate idiot"*, *"I know people call me a dork and that's okay with me"*. Twitter users also attach a stigma to themselves with an ironic tone. Examples are *"I am an idiot savant"*, *"Workaholic man with ADHD"*, *"I didn't choose the nerd life, the nerd life chose me"*.

Social identity categories are not mutually exclusive. Individuals may have more than one social identity and embed all identities in their definition of the self. On Twitter, it is common to find users who express more than one identity in the profile description. For example, *“Mom of 2 boys, wife and catholic conservative, school and school sport volunteer”, “Proud Northerner, Arsenal fan by luck. Red Level and AST member. Gamer. Sports fan. English Civic Nationalist. Contributor at HSR. Pro- #rewilding”*.

4.3 Data collection

We collected data by randomly sampling English tweets. From the tweets, we retrieved the user’s profile description. We removed all profiles (i.e., 30% of the total amount of retrieved users’ profiles) where no description was provided.

We are interested in developing an automatic classification tool (i.e., social identity classifier) that can be used to study identities of both people engaged in online collective action and general Twitter users. For this purpose, we used two different sources to collect our data: (1) English tweets sent during the 2013 and 2014 editions of the Movember cancer awareness campaign, which aims at changing the image of men’s health (i.e., prostate and testicular cancer, mental health and physical inactivity)¹⁴; and (2) English random tweets posted in February and March 2015 obtained via the Twitter Streaming API. We selected the tweets from the UK, US and Australia, which are the three largest countries with native English speakers. As on Twitter only 2% of tweets are geo-located, we used a country classifier that predicts that was found to be accurate in predicting tweets’ geolocation for these countries (Van der Veen, Hiemstra, van den Broek, Ehrenhard, & Need, 2015).

From these two data sources, we obtained two Twitter user populations: Movember participants and random generic users. We randomly selected profiles from these two populations for our text classification experiments. Our final dataset consists of 2,633 Twitter users’ profile descriptions (1,611 Movember profiles and 1,022 random profiles).

4.4 Methods

In this study, we combined qualitative content analysis with human annotation (Section 4.4.1) and text classification experiments (Section 4.4.2).

¹⁴ This data was obtained via a Twitter datagrant, see Section 1.5 in the Introduction.

4.4.1 Qualitative content analysis with human annotation

We used qualitative content analysis to manually annotate the 2,633 Twitter users' profile descriptions of our sample. Two coders were involved in the annotation. The coders met in training and testing sessions to agree upon rules and build a codebook¹⁵ to guide the annotation. The identity categories of our codebook were based on the five-category social identity classification described in Section 4.2. In the annotation, a Twitter profile description was coded depending on whether the profile belongs to such category (Yes = 1) or not (No = 0). Multiple identities could be assigned to a single Twitter user (i.e., identity categories were not mutually exclusive). We calculated the inter-rater reliability using Krippendorff's alpha¹⁶ (Krippendorff, 2004) based on 300 double annotations. Kalpha values were very good for all categories (Relational=0.902; Occupational=0.891; Political=0.919; Ethnic/Religious=0.891; Stigmatized=0.853).

As our definition of social identity was applicable only to individuals, accounts related to more than one person, or to collectives, groups, or organizations (N=280), were annotated as "Not applicable" (Kalpha=0.8268). Such a category also included individual profiles (N=900) for which no social identity category fitted (e.g., profiles contain quote/citations/self-promotion; or individual attributes descriptions with no reference to social roles or group membership); or for ambiguous or incomprehensible cases¹⁷.

Looking at the distributions of social identity categories in the annotated profile descriptions provides an overview of the types of Twitter users in our data. Figure 4.1 shows the distributions of social identity categories over the total amount of annotated profiles (N=2,633). As the figure shows, that each identity category is similarly distributed in the two populations (i.e., Movember participants and random generic users), which thus are similar in terms of social identities. More specifically, users mainly define themselves on the basis of their occupation or interests (occupational identities=36%), and social roles played in society or relationships with others (relational identities=28%). By contrast, individuals do not often describe themselves in terms of political or social movement affiliation, ethnicity, nationality, religion, or stigmatized group membership. Political, ethnic/religious and stigmatized identities categories are less frequent (respectively, 4%, 13% and 7%). N/a profile descriptions are the 45% (N=1180) of the total number of profiles: organizations/collective profiles are 11% (N=280), whereas no social identity

¹⁵ The codebook and the Python script used in the experiments are available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

¹⁶ We use Krippendorff's alpha as it is considered the most reliable inter-coder reliability statistic in content analysis.

¹⁷ We kept N/a profiles in our dataset to let the classifiers learn that those profiles are not examples of social identities. Such choice considerably increased the number of negative examples over the positive ones that were used to detect the identity categories. However, including or excluding N/a profiles did not make any significant difference in the classifier's performance.

profiles/ambiguous cases are 34% (N=900). It means that only a little more than a half, i.e., the remaining 55% profiles (N=1,453), of the Twitter users in our dataset have one or

Figure 4.1 Distributions (in %) of social identity categories over the total amount of annotated profiles (N=2,633): Movember participants population, random generic users population and total distribution.

more social identities.

4.4.2 Automatic text classification

We used machine learning to automatically assign the predefined identity categories to 160-character Twitter profile descriptions (N=2,633). As we want to classify whether the profile description belongs to a category or not, we treated the social identity classification as a binary text classification problem, where each class label could take only two values (Yes = 1; No = 0).

We used automatic text classification and developed binary classifiers in two experiments. Experiment 1 was based on the five-category social identity classification explained in Section 4.2. In Experiment 1, we compared the classifiers performance in two scenarios. First, we used a combined dataset made by both Movember participants and random generic users. Profiles were randomly assigned to a training set (Combined(1): N=2338) and a test set (Combined(2): N=295). Second, we used separated datasets, i.e., random generic users as training set (Random: N=1022) and Movember participants as test set (Movember: N=1611), and vice versa.

Experiment 2 was a follow-up of Experiment 1 and we used only combined data¹⁸. We tested a combination of three social identity categories (i.e., political, ethnic/religious and stigmatized) for which we did not obtain acceptable results in Experiment 1.

Features extraction. We used TF-IDF weighting (Salton & Buckley, 1988) to extract useful features from the user's profile description. We measured how important a word, or term, is in the text. Terms with a high TF-IDF score occur more frequently in the text and provide the most of information. In addition, we adopted standard text processing techniques, such as Lowercasing and Stop words, to clean up the feature set (Sebastiani, 2002). We used the Chi Square feature selection on the profile description term matrix resulted from the TF-IDF weighting to select the terms that are mostly correlated with the specific identity category (Sebastiani, 2002).

Classification algorithms. In the automatic text classification experiments, we evaluated four classification algorithms. First, we used Support Vector machine (SVM) with a linear kernel. The SVM requires less parameters to optimize and is faster compared to other kernel functions, such as Polynomial kernel (Joachims, 1998). Balanced mode was used to automatically adjust weights for class labels. Second, Bernoulli Naïve Bayes (BNB) was applied with the Laplace smoothing value set to 1. Third, Logistic Regression (LR) was trained with balanced subsample technique to provide weights for class labels. Fourth, the Random Forest (RF) classifier was trained with 100 trees to speed up the computation compared to a higher number of trees, for which no significant difference was found in the classifier performance. Balanced subsample technique was used to provide weights for the class labels.

Evaluation measures. Experimental evaluation of the classifiers was conducted to determine their performance, i.e., the degree of correct classification. We compared the four classification algorithms (SVM, BNB, LR, RF) on the training sets using the Stratified 10-Fold Cross Validation. This technique seeks to ensure that each fold is a good representative of the whole dataset and it is considered better than regular cross validation in terms of bias-variance trade-offs (Kohavi, 1995). In feature selection, we checked for different subsets of features (i.e., 500, 1000, 2000, 3000, 4000 and 5000) with the highest Chi Square from the original feature set, which consists of highly informative features. We found that 1000 features are the most informative. Furthermore, we calculated precision (P), recall (R) and F-score to assess the accuracy and completeness of the classifiers. The classification algorithm that provided the best performance according to F-score in the

¹⁸ We conduct Experiment 2 only on the combined set because in Experiment 1 we find that classifiers trained on the combined data performs better than trained on separated sets.

Stratified 10-Fold Cross Validation was then tested on the test sets to get better insight into the classification results.

4.5 Classification experiment 1

In this section, we present the results of the Experiment 1 on automatically identifying five online social identities based on the annotated Twitter profile descriptions. In Section 4.5.1, we show the results of the Stratified 10 Fold Cross Validation in the three training sets, i.e., Combined(1), Movember and Random. In Section 4.5.2, we illustrate and discuss the results of the best classification algorithm on the test sets.

4.5.1 Stratified 10-Fold cross validation results on five social identity categories

Relational identity. All classifiers provide very precise results ($P > 0.700$) for the relational identity category in all three training sets (Table 4.1). The most precise classification algorithm is BNB in the combined set ($P = 0.855$). By contrast, recall is quite low ($0.500 < R < 0.700$) in all classifiers in each training set, thus affecting the final F-scores. The classification algorithm with the highest recall is LR in the Movember set ($R = 0.708$). According to F-scores, all classifiers provide from acceptable ($0.400 < F < 0.690$) to good/excellent ($F > 0.700$) results. Classifiers trained on the Movember set provide the highest F-scores, except for BNB, for which the F-score is higher in the combined set. The Random set, instead, provides the lowest performances in all cases. Overall, the LR algorithm is the most precise and complete classifier in all three training sets (combined: $F = 0.724$; Movember: $F = 0.735$; Random: $F = 0.637$).

Occupational identity. All classifiers provide very high precision ($P > 0.800$) and recall ($R > 0.750$) for the occupational identity category (Table 4.1). The most precise classification algorithm is BNB in the Random set ($P = 0.859$), whereas the classification algorithm with the highest recall is SVM in the combined set ($R = 0.793$). According to the F-scores, all classifiers provide good and excellent performances ($F > 0.700$), except for BNB in the Random set ($F = 0.599$). Classifiers trained on the combined set provide the highest F-scores, except for BNB, for which the F-score is higher in the Movember set. By contrast, the Random set provides the lowest performances. Overall, SVM and LR provide the best F-scores in all three training sets.

Table 4.1. Relational and occupational identities. Stratified 10-Fold Cross Validation in three training sets: precision (P), recall (R) and F-score.

<i>Classifier</i>	<i>Training Set</i>	RELATIONAL			OCCUPATIONAL		
		P	R	F	P	R	F
SVM	Combined(1)	0.764	0.705	0.723	0.827	0.793	0.804
	Movember	0.792	0.709	0.729	0.822	0.788	0.797
	Random	0.742	0.624	0.634	0.845	0.715	0.742
BNB	Combined(1)	0.855	0.635	0.652	0.848	0.769	0.788
	Movember	0.848	0.616	0.619	0.846	0.780	0.791
	Random	0.793*	0.524	0.471*	0.859	0.605	0.599
LR	Combined(1)	0.760	0.708	0.724	0.823	0.788	0.800
	Movember	0.786	0.718	0.735	0.817	0.789	0.796
	Random	0.717	0.627	0.637	0.848	0.721	0.748
RF	Combined(1)	0.803	0.660	0.682	0.842	0.780	0.797
	Movember	0.836	0.671	0.692	0.817	0.774	0.783
	Random	0.789	0.583	0.577	0.857	0.706	0.733

* These values are examples cases where SVM, BNB and RF classified the profile in one of the 10 folds to not belong to the identity class.

Table 4.2. Political, ethnic/religious and stigmatized identities. Stratified 10-Fold Cross Validation in three training sets: precision (P), recall (R) and F-score.

<i>Classifier</i>	<i>Training Set</i>	POLITICAL			ETHNIC/RELIGIOUS			STIGMATIZED		
		P	R	F	P	R	F	P	R	F
SVM	Combined(1)	0.646*	0.548	0.563*	0.750	0.594	0.619	0.713*	0.551	0.573*
	Movember	0.680*	0.529	0.541*	0.740	0.585	0.609	0.825	0.592	0.629
	Random	0.528*	0.510	0.505*	0.784	0.581	0.602	0.520*	0.507	0.498*
BNB	Combined(1)	0.482	0.500	0.491	0.572*	0.506	0.483*	0.478	0.500	0.488
	Movember	0.479*	0.500	0.489*	0.664	0.512	0.491	0.561*	0.507	0.494*
	Random	0.478	0.500	0.488	0.432	0.500	0.463	0.470	0.500	0.484
LR	Combined(1)	0.662	0.540	0.554	0.724	0.600	0.626	0.781	0.564	0.593
	Movember	0.655	0.536	0.550	0.720	0.603	0.628	0.742	0.589	0.621
	Random	0.528	0.509	0.505	0.751	0.592	0.613	0.520	0.506	0.498
RF	Combined(1)	0.633*	0.524	0.532*	0.856*	0.526	0.523*	0.654	0.519	0.524*
	Movember	0.479*	0.500	0.489*	0.848*	0.551	0.560*	0.884*	0.585	0.623*
	Random	0.478*	0.500	0.488*	0.672	0.524	0.508	0.470*	0.500	0.484*

* These values are examples cases where SVM, BNB and RF classified the profile in one of the 10 folds to not belong to the identity class.

Table 4.3. LR Classifier Testing on relational and occupational identities: precision (P), recall (R) and F-score.

Training Set	Test Set	RELATIONAL			OCCUPATIONAL		
		P	R	F	P	R	F
Combined(1) Member Random)	Combined(2)	0.757	0.648	0.699	0.743	0.791	0.766
	Member	0.649	0.491	0.559	0.722	0.693	0.707
	Random)	0.638	0.555	0.594	0.814	0.673	0.737

Table 4.4 LR classifier testing on political, ethnic/religious and stigmatized identities: precision (P), recall (R) and F-score.

Training Set	Test Set	POLITICAL			ETHNIC/RELIGIOUS			STIGMATIZED		
		P	R	F	P	R	F	P	R	F
Combined(1) Member Random)	Combined(2)	0.600	0.200	0.300	0.661	0.460	0.543	0.958	0.273	0.425
	Member	0.571	0.173	0.266	0.531	0.300	0.383	0.360	0.145	0.206
	Random)	0.307	0.058	0.098	0.364	0.250	0.296	0.444	0.126	0.197

Political, ethnic/religious and stigmatized identities. The classifiers perform less well in automatically classifying political, ethnic/religious and stigmatized identities than in relational and occupational ones (Table 4.2). Both precision and recall are almost acceptable ($0.400 < P$ and $R < 0.690$) in all three training sets. In some cases, SVM, BNB and RF classify each profile in one of the 10 folds to not belong to the identity class. In this case, we decide that precision, recall and F are all 0 on that fold, although strictly speaking, precision, recall and F are not defined in these cases (in Table 4.2, these values are marked with a *). As we noticed earlier in Figure 4.1, the low number of positive examples of political, ethnic/religious and stigmatized identities in the data may cause this outcome. The classifiers trained on the combined and Movember sets provide similar results, whereas the Random set provides the lowest performance. Overall, the LR classifier provides the best F-scores for each category in all training sets.

4.5.2 LR classifier testing

The Stratified 10-Fold Cross Validation shows that the optimal classification algorithm for each identity category is the LR. The LR classifier is evaluated on the test sets in order to get better insight into the classification results. Since we use three training sets, we evaluate the classifier on three different test sets as explained in Section 4.4.2.

According to the F-scores (Table 4.3), we are able to automatically classify relational and occupational identities in all three test sets. The LR trained and tested on combined data provides the best results (relational: $F=0.699$; occupational: $F=0.766$). Although in the Stratified 10-Fold Cross Validation the classifier trained on the Random set has lower performance than trained on the Movember set, in the final testing the classifier performs better when we use Random as training set and Movember as test set (relational: $F=0.594$; occupational: $F=0.737$).

The final training and testing using LR on political, ethnic/religious and stigmatized identities (Table 4.4) is affected by the low number of positive examples in the test sets, as these identities are less frequent in our annotated sample. Classifying political identities is the most difficult task for the classifier in all three test sets and the performance is very low (Combined(2): $F=0.300$; Random: $F=0.266$; Movember: $F=0.098$). Regarding ethnic/religious and stigmatized identities, the LR provides almost acceptable F-scores only on the combined data (Ethnic religious: $F=0.543$; Stigmatized: $F=0.425$).

4.5.3 Discussion: merging identity categories

In Experiment 1, we showed that a classifier trained on the combined data performs better than a classifier trained on only Movember profiles or Random profiles. Our results are of sufficient quality for relational and occupational identities on the combined set, and

thus we were able to automatically classify such social identities on Twitter using LR. Experiment 1 also shows that automatically classifying political, ethnic/religious and stigmatized identities was a challenging task. Although the LR provided acceptable F-scores in the Stratified 10-Fold Cross Validation, the classifier was not able to automatically classify those three identities. This may be caused by unbalanced distributions of identity categories in our data, thus affecting the text classification experiment.

Owing to the unsatisfactory classifier performances in detecting political, ethnic/religious and stigmatized identities, we conducted a second experiment where we merged political, ethnic/religious and stigmatized identities in one category, called *collective action-oriented identities* (N=556). People with strong political, ethnic/religious and stigmatized identities are often more engaged in online and offline collective action (Ren, Kraut, & Kiesler, 2007; Spears, Lea, Corneliussen, Postmes, & Ter Haar, 2002). These identities have a collective, rather than individualistic, nature as they address individual membership to one or multiple social groups. By sharing a common identity with other group members, individuals may feel more committed to the group's topic or goal. Consequently, they may engage in collective action on behalf of the group, even in cases of power struggle, i.e., individuals have a politicized identity (see Klandermans, Sabucedo, Rodriguez, & De Weerd, 2002; Simon & Klandermans, 2001). Political, ethnic/religious and stigmatized identities are indeed action-oriented (Ren et al., 2007), rather than social statuses as for Relational and Occupational identities (Deaux et al., 1995). Thus, the collective, action-oriented nature of certain political, ethnic/religious and stigmatized identities show how such identities may often overlap and consequently influence human behaviors and actions. Following these theoretical arguments, we merged political, ethnic/religious and stigmatized identities because of their importance in the study of collective action. In this way, we also provided more positive examples to the classifiers. In Experiment 2, we trained and tested the four classification algorithms on the collective action-oriented identity using the combined data. In the next section, we present the results of this second experiment and show that by combining these identities we can improve the predictive performance of the classifiers.

4.6 Classification experiment 2

Table 4.5 shows the values of precision recall and F-score using the Stratified 10-Fold Cross Validation on the training set (i.e., Combined (1): N=2338) to select the optimal classifier. Overall, all classifiers provide acceptable performances for the collective action-oriented identity category ($0.500 < F < 0.650$). RF is the most precise classification algorithm

($P=0.758$), whereas LR has the highest recall ($R=0.608$). As in Experiment 1, the LR is the optimal classifier with the highest F-score ($F=0.623$).

The LR classifier is evaluated on the test set (i.e., Combined (2): $N=295$) to get better insight into the classification results. The classifier is highly precise in identifying collective action-oriented identities ($P=0.857$). By contrast, recall is quite low ($R=0.466$), thus affecting final F-score ($F=0.604$). In conclusion, only if we merge political, religious and stigmatized identities, the classifier performance is acceptable.

Table 4.5. Collective action-oriented identity. Stratified 10-Fold Cross Validation on combined data: precision (P), recall (R) and F-score.

<i>Classifier</i>	P	R	F
SVM	0.664	0.583	0.595
BNB	0.750	0.524	0.504*
LR	0.678	0.608	0.623
RF	0.758	0.543	0.540

* These values are examples cases where SVM, BNB and RF classified the profile in one of the 10 folds to not belong to the identity class.

4.7 Final discussion and conclusions

In this study, we explored the task of automatically predicting and classifying Twitter social identities of Movember participants and random generic users in two text classification experiments. We were able to automatically classify two identity categories (relational identity and occupational identity) and a 3-identity category combination (collective action-oriented identity). Furthermore, we found that a classifier trained on the combined data performs better than a classifier trained on one group (e.g. Random) and test on the other one (e.g. Movember).

We make two main contributions from which both social theory on identity and NLP methods can benefit. First, by combining NLP and social theory we find that social theory can be used to guide NLP methods to quickly classify and infer vast amounts of data in social media. Furthermore, we show that NLP methods can provide input to revisit traditional social theory that is often strongly consolidated in offline settings (see Experiment 2).

Second, we show that computers can perform a reliable automatic classification for most types of social identities on Twitter. In NLP research, there is already much earlier work on inferring demographic traits, therefore it may not be surprising that at least some of these identities can be easily inferred on Twitter. Nonetheless, in our experiment with three social identities (Experiment 2) we show that a combination of identities is useful features to improve the predictive performance of the classifiers. In such way, we provide social scientists with three social identity classifiers (i.e., relational identity, occupational identity, and collective action-oriented identity) grounded in social theory that can scale-

up online identity research to massive datasets. Social identity classifiers may assist researchers interested in the relation between language and identity, and identity and collective action. In practice, they can be exploited by organizations to target specific audiences and improve their campaign strategies.

Our study presents some limitations that future research may address and improve. First, we retrieved the user's profile description from randomly sampled tweets. In this way, people who tweet a lot have a bigger chance of ending up in our data. Future research could explore alternative ways of profile description's retrieval that avoid biases of this kind.

Second, our social identity classifiers were based only on 160-characters profile descriptions, which alone may not be sufficient features for the text classification. We plan to test the classifiers also on tweets, other profile information and network features. Furthermore, the 160-character limitation constrains Twitter users to carefully select which identities to express in such a short space. In our study, we did not investigate identity salience, that is, the degree or probability that an identity is more prominent than others in the text. Future research that combines sociolinguistics and NLP methods could investigate how semantics are associated to identity salience, and how individuals select and order their multiple identities on Twitter texts.

Third, in the experiments we used standard text classification techniques that are not particularly novel in NLP research. However, they are effective ways to provide input for social theory. We plan to improve the classifiers performance by including other features, such as n-grams and word clustering. Furthermore, we will explore larger datasets and include more training data for further experimentation with more complex techniques (e.g., neural networks, Word2Vec).

Chapter 5

“Grow a #Mo and Save a Bro”: The Effect of Online Social Identity and Communication Network Position on Donations Collected during a Health Advocacy Campaign

Earlier versions of this chapter were presented at the *American Sociological Association Annual Meeting* in Philadelphia (Priante, Ehrenhard, Van Den Broek, Need, & Hiemstra, 2018), the *Annual Meeting of the Academy of Management* in Chicago (Priante, Need, Van Den Broek, & Hiemstra, 2018), and the *Health by Tech Conference* (Priante, Need, Ehrenhard, Van Den Broek, & Hiemstra, 2018).

Abstract

Social movement organizations use social media to mobilize people for social causes. However, little is known about the micro-level mechanisms driving individual mobilization outcomes that require a substantial effort, such as collecting donations during advocacy campaigns. In this paper, we investigate two factors that we deem critical to explaining such outcomes: social identity as a motivator to engage in campaigns and communication networks as providers of opportunity structures for mobilization. Using the 2014 US Movember health campaign on Twitter as an empirical context, we investigate the effects of three types of online social identity (relational, occupational, and collective action-oriented) and communication network positions on the individual amount of collected donations for prostate and testicular cancer research during the campaign. To this end, we adopt a multimethod approach that combines automatic text analysis, social network analysis, and multivariate regression analysis. We find that only occupational identity had a significant, positive effect on the amount of collected donations, whereas there were no significant effects for relational identity and collective action-oriented identity. In terms of network positions, the results show that, while occupying central positions in the Twitter communication network facilitated mobilization outcomes, the people at the core of network communities collected less in donations than people at the periphery. We show the importance of integrating the study of identity and networks to advance our understanding of online micro-mobilization dynamics and the effectiveness of online social movement campaigns. We offer contributions to research on social movements, media and communication, health fundraising, and philanthropy.

5.1 Introduction

Social movement organizations (SMOs) use social media to mobilize people for social causes (Earl, 2015; Earl et al., 2014; Murthy, 2018; Walker & Martin, 2018), such as advocacy campaigns to promote health. For example, the Movember Foundation is an SMO that organizes a campaign every November to promote awareness of prostate and testicular cancer (Movember, 2014). The foundation uses the symbol of the moustache to make people identify with the cause and construct a collective identity in order to foster participation in campaign activities, such as collecting donations for medical research. Social media like Twitter are used to promote the campaign, motivate people to participate, encourage them to talk about health, and engage in fundraising for the movement's cause (Bravo & Hoffman-Goetz, 2015; Jacobson & Mascaro, 2016; Prasetyo et al., 2015; van den Broek et al., 2018).

Research finds that social media provide effective tools to organize and communicate about collective action in fast and cheap ways (Bennett & Segerberg, 2012; Earl et al., 2014; Tufekci & Wilson, 2012; Van Laer & Van Aelst, 2010). While some scholars find that social media activism moves people from the online world into the streets, others criticize online mobilization as a form of “slacktivism” (Morozov, 2009) or “clicktivism” (White, 2010), that is, low-effort and low-cost actions that have little or no impact on meaningful offline action (Karpf, 2012; Lewis et al., 2014; Noland, 2017). In this debate, we know little about the online micro-level mechanisms driving the individual mobilization outcomes that require a substantial effort. Our paper addresses this gap by investigating two factors – social identity and communication network position – that we find critical to explaining online individual mobilization outcomes that require a substantial effort, such as collecting donations for medical research. On the one hand, we posit that online social identity provides people with the motivation to engage in fundraising during advocacy campaigns organized by SMOs. On the other hand, we argue that networks provide opportunity structures that can be beneficial (or detrimental) to achieving successful outcomes. Studying these mechanisms is important because it deepens our understanding of the conditions under which online social movement campaigns are effective at achieving their desired goals (Boulianne, Minaker, & Haney, 2018; Earl, 2015; Earl et al., 2014; Elliott & Earl, 2018; Rohlinger & Bunnage, 2015, see Chapters 1 and 3 of this dissertation). The research question in this chapter is:

Question 5: How and why do movement members' online social identity and structural position in the communication network influence the individual amount of collected donations during online campaigns?

Our empirical context is the 2014 US Movember campaign on Twitter organized to raise donations for research on prostate and testicular cancer. Our unit of analysis is individuals who participated in the campaign on Twitter and were officially registered members of the Movember Foundation. This paper examines how and why movements members’ online social identity and communication network position influence the individual amount of collected donations during the campaign. To answer this question, we adopt a multimethod approach that combines automatic text analysis, social network analysis, and multivariate regression analysis. This research shows the importance of integrating the study of identity and network to advance our understanding of online micro-mobilization dynamics and the effectiveness of online social movements campaigns (see Chapter 2 and 3 of this dissertation). We offer contributions to research on social movements, media and communication, health fundraising, and philanthropy.

5.2 Theory and hypothesis

Scholars studying online mobilization dynamics argue in favor of combining motivational and structural factors in order to explain the mechanisms driving people’s engagement in collective action via social media (Gerbaudo & Treré, 2015; Kende et al., 2016; LeFebvre & Armstrong, 2016, Chapter 2 of this dissertation), in particular when it requires some effort, such as volunteering or collecting donations for social causes (Bekkers & Wiepking, 2011). In social movement research, collecting donations is considered an active form of participation that requires a financial contribution involving some risk and effort (Garrett, 2006; Van Laer & Van Aelst, 2010). Scholars find that social media are effective means to promote charitable behavior (Boulianne et al., 2018). To understand how people mobilize in social media to achieve these types of goals, we focus on two widely cited factors known to affect individual mobilization outcomes such as collecting donations: social identity and communication network position.

5.2.1 Online social identity as a motivator to collect donations

Social identity is an individual’s self-concept derived from social roles or categories (Stryker et al., 2000) and memberships of social groups (Tajfel, 1978). Social movement research has a long tradition of studying the role of social identity as a socio-psychological predictor that explains why people decide to participate in collective action (van Stekelenburg & Klandermans, 2013; van Zomeren et al., 2008). While studies focusing on online mobilization find that social identities foster low-threshold collective action, such as signing an online petition, there are mixed findings on whether this translates into more

meaningful forms of participation (for a review, see Chapter 2 of this dissertation), such as collecting donations for social causes.

As people might have more than one social identity, an identity becomes salient when a person invoke such an identity in a certain situation (Davis, 2016). When an identity is salient, such an identity guides actions (Davis, 2016; Stets & Carter, 2012). In other words, an identity's predictive power on human actions depends on the context that influences which identity becomes salient and important at the moment people decide which action to take. Here, we look at the types of social identities becoming salient online in order to understand how they can function as motivators for people to collect donations during online campaigns.

Research shows that social media offer open, free platforms for identity expression and formation (Davis, 2016; Papacharissi, 2010). For example, in Twitter profile descriptions, people provide information about their identity in terms of professions, interests, political orientation, or familial relationships; in this way, they have particular salient identities online. In Chapter 4, we developed a classification of the most typical types of social identity that can be found in social media contexts: relational identity, occupational identity, and collective action-oriented identity.

First, relational identity is a self-definition based on reciprocal or non-reciprocal relationships that an individual has with other people (Deaux et al., 1995). Examples are family (e.g., being a mother or a husband), friendships, and fan-ship (e.g., being a fan of an actor or a football team). Having a salient relational identity means priming one's identity as based on the importance of relationships with others. Previous research investigating the relation between family roles and donating to or volunteering at cancer-related events finds that having a relational identity increases the chances of engaging in pro-social behavior when a person has a family member with cancer (Aaker & Akutsu, 2009) or feels the pressure of being asked to donate by family members whom the person cares about (Wheeler, DeMarree, & Petty, 2007). More broadly, knowing a person in need is positively associated to the likelihood of donating to a social movement or non-profit organization related to that cause (Bekkers & Wiepking, 2011). Other scholars show that identification with parental roles makes people more likely to donate money and engage in philanthropy (Bekkers, 2007; Bekkers & Wiepking, 2011). Therefore, we posit that there is a positive association between having a salient relational identity and the collected donations:

H1a: Movement members with a salient online relational identity collect higher amounts of donations in online advocacy campaigns than members without a salient online relational identity.

Second, occupational identity is a type of social identity that stands for a self-definition based on an individual's occupation, profession, career, or membership(s) of communities of practice meant as informal social entities emerging from individual vocations, avocations, interests, and hobbies (Deaux et al., 1995; Skorikov & Vondracek, 2011). Because of the importance of work, occupation, and vocations in people's lives (Skorikov & Vondracek, 2011), occupational identity is acknowledged as one of the most important core components of an individual's identity. Research finds that occupational identity orients and influences actions related not only to people's work but also to other behaviors, such as volunteering (Bekkers & Wiepking, 2011). Scholars have shown that money donors tend to be employed people with high levels of education and income (Bekkers & Wiepking, 2011; Shehu, Langmaack, Felchle, & Clement, 2015; Wiepking & Bekkers, 2010), which are characteristics often associated with salient occupational identities. Employee volunteering in civic associations is also a topic of interest in the study of social movements outcomes (Walker, McCarthy, & Baumgartner, 2011). In addition, scholars find that people with utilitarian, business-driven identities are often the target of non-profit organizations as they are more likely to engage in donation behavior than people who have only an emotional attachment to the cause (Aaker & Akutsu, 2009; Lee & Bourne, 2017). Therefore, we posit that there is a positive association between having a salient occupational identity and collected donations:

H1b: Movement members with a salient online occupational identity collect higher amounts of donations in online advocacy campaigns than members without a salient online occupational identity.

While relational and occupational identities are mostly considered as individual, social statutes, other social identity types have a more collective and action-oriented nature (Deaux et al., 1995, see Chapter 4 of this dissertation). For example, political identities denote self-definitions based on political affiliations, parties, and groups, as well as being a member of a social movement or participating in collective action (Klandermans et al., 2002; van Stekelenburg & Klandermans, 2013). Studies show that political participation and affiliation are positively associated with activities in voluntary associations (Bekkers, 2005; Walker, 2008) and that people with a politicized identity are more likely to engage in collective action on behalf of the group, even in cases of a power struggle (Klandermans et al., 2002; Simon & Klandermans, 2001; van Stekelenburg & Klandermans, 2013). In addition, scholars find that ethnic-religious identities, as self-definitions based on membership of ethnic or religious groups (Deaux et al., 1995), correlate positively with people's engagement in donation behavior and volunteering (Bekkers & Schuyt, 2008; Shehu et al., 2015; Wiepking & Bekkers, 2010). In online contexts, these identities often

overlap due to their collective action–oriented nature (see Chapter 4 of this dissertation). Research finds that individuals with strong political, ethnic, or religious identities are the ones more often engaged in both online and offline collective action (Ren et al., 2007; Spears et al., 2002). Therefore, we posit that there is a positive association between having a salient collective action–oriented identity (political, ethnic, or religious) and collected donations:

H1c: Movement members with a salient online collective action–oriented identity collect higher amounts of donations in online advocacy campaigns than members without a salient online relational identity.

5.2.2 Communication network position as a provider of opportunity structures to collect donations

Network ties are important predictors of participation and engagement in social movements as they provide opportunity structures that can facilitate or constrain mobilization (González-Bailón et al., 2013; González-Bailón & Wang, 2016). The formation of relational ties via communication networks is a consolidated topic in network theory and is applied in several studies on collective action and social media (e.g., Bimber et al., 2005; González-Bailón & Wang, 2016; Mattoni & Treré, 2014). Social media provide people with the space to engage in communication processes that are useful to organize and coordinate collective action (Bennett & Segerberg, 2012). People create relations with others via communication processes and, thus, generate communication networks where people are nodes and the messages they exchange are relational ties. From how people communicate in social media, it is possible to derive their communication network positions, which are important to understand individual performance (Buskens & van de Rijt, 2008; Kalish & Robins, 2006; Sasovova, Mehra, Borgatti, & Schippers, 2010), such as collecting donations (Bekkers & Wiepking, 2011; Boulianne et al., 2018, see Chapter 3 of this dissertation).

Scholars typically use two concepts to identify individuals' network positions: centrality and core-periphery. Centrality stands for an actor's importance and relevance in the communication network (Freeman, 1979), whereas core-periphery distinguishes between people's positions in network layers, such as a core of cohesive and densely connected actors and the periphery of loosely connected actors (Borgatti & Everett, 2000). Together, these two concepts provide a robust structural assessment of network positions because they provide a complementary understanding of communication network structures (Borgatti & Everett, 2000).

Centrality is traditionally used in the study of online networks as an indicator of people's influence and success in mobilization (Centola, 2013; Diani & McAdam, 2003;

González-Bailón & Wang, 2016). Scholars find that people who are central in the network exert power, authority, and control over communication flow (Pavan, 2017) and play a determining role in spreading conversations through mobilization (Jacobson & Mascaro, 2016). There are several ways to address centrality, and scholars argue that the concept of harmonic centrality is the most appropriate to identify central people in large, sparse networks (Boldi & Vigna, 2014; Rochat, 2009), such the communication networks derived from social media campaigns (González-Bailón & Wang, 2016). Harmonic centrality defines central actors as people who are close to and very well connected with others in the network who are also well-connected and important (Rochat, 2009). Consequently, when people are close to many others, there is no need to rely on intermediaries or brokers (Burt, 2012). People with a high closeness centrality have high communication potential because it is easier for them to reach out to many others than people who are less central. In this way, they can exploit their numerous contacts to collect more donations. Hence:

H2a: The more central a movement member is in the communication network, the higher will be the total amount of collected donations.

Closely related to centrality, a core-periphery structure identifies subgroups of people who occupy structurally equivalent positions in the network (Borgatti & Everett, 2000). Core-periphery structures are found in studies of online communities (Johnson, Safadi, & Faraj, 2015) and communication networks formed during online mobilization (Barberá et al., 2015). Research finds that people situated at the network core of a community are embedded in their social system, that is, they are deeply immersed in cohesive network regions characterized by strong ties (Cattani & Ferriani, 2008; Dahlander & Frederiksen, 2011). In this way, they can leverage credibility and recognition from others and, thus, obtain their support by exploiting these strong ties (Cattani & Ferriani, 2008; Dahlander & Frederiksen, 2011; Uzzi, 1997). However, positions at the core might backfire (Cattani & Ferriani, 2008; Dahlander & Frederiksen, 2011). The redundancy of strong ties at the core signals the presence of very similar individuals who, to a certain extent, might aim at achieving the same goal (e.g., collecting donations) by communicating with the same audience. In other words, members at the core are fundraisers surrounded by many other fundraisers. Members at the periphery, by contrast, are more dispersed and belong to less well-connected regions, which are characterized by weak ties and are often more crucial to information transmission than strong ties (Centola, 2010; Granovetter, 1973; Onnela et al., 2007). Peripheral members are surrounded by less homogenous audiences and, although they have less visibility than people at the core, they exploit their weak ties to link various others, get new resources to mobilize, and solicit more diverse audiences to

support their cause (Bekkers & Wiepking, 2011; Granovetter, 1973; Hargadon, 2006). In this vein, we argue that holding a position too close to the core might have negative effects on mobilization aimed at acquiring resources, such as collecting donations.

H2b: The closer a movement member is to the core of the communication network, the lower will be the total amount of collected donations.

5.3 Methods

5.3.1 Research setting and data

The research setting of this study is the 2014 US Movember campaign on Twitter. The campaign is organized every November by the Movember Foundation, a social movement and non-profit organization founded in 2003 in Australia to promote awareness of and conversations about men's cancer and collect donations for medical research. We focus on the US campaign as the USA is one of the first countries where the movement spread, and year after year it has the highest amount of collected donations worldwide (Movember, 2014). We focus on the campaign on Twitter because Twitter is an important tool that the foundation uses to promote the campaign (Bravo & Hoffman-Goetz, 2015; Jacobson & Mascaro, 2016; van den Broek et al., 2018).

The Movember Foundation allows people to become official members (MoBros and MoSistas) via a free website subscription, open a personal webpage to share their fundraising activities, and link this page to their social media accounts (Movember, 2014). The population of this study consists of officially registered members (N=3,295) who participated in the 2014 US Movember campaign on Twitter by sending at least one tweet. The selected time span stretches from two weeks before the beginning of the campaign (15 October) to two weeks after the end of the campaign (15 December). Members can both donate money themselves to the Movember Foundation and solicit others to donate. In this sense, they can be considered fundraisers. However, not all members were successful in their fundraising: During the 2014 US campaign, 19.79% of the members did not collect any donations.

For this study, we used data from two sources. First, we obtained Twitter data, such as users' Twitter activity and profile description information, via a Twitter datagrant on large online cancer awareness campaigns, including Movember (see the Introduction, Section 1.5). From this database, we retrieved tweets based on the US geographical location, sent between 15 October 2014 and 15 December 2014, and containing Movember-related hashtags.¹⁹ This resulted in a dataset of 14,970 tweets sent by 3,295 Movember members.

¹⁹ More information on the Twitter data collection and preparation are provided in Appendix B at the end of this dissertation.

Second, we obtained Movember data, such as members’ total amount of collected donations, years of experience in the campaign, and gender, from the US Movember Foundation. We merged the Twitter and Movember data by linking movement members’ accounts on the Movember website to their Twitter accounts (Nguyen et al., 2015).

5.3.2 Measures

Total amount of collected donations. The dependent variable of this study is the total amount of money in US dollars collected by each Movember member during the campaign (15 October 2014–15 December 2014) via online sources. This individual amount of donations is derived from both personal donations and other people donating to the members. The variable ranges from 0 to 60,946 US dollars. We log-transformed the variable to reduce skewness (Zumel & Mount, 2014), used the natural logarithm, and added a small constant (+1) to handle cases where the variable was equal to 0.

Online social identity. Our first set of key variables features Movember members’ online social identity. Previous research shows that users’ profile descriptions in social media are the most immediate, essential expressions of their online salient identity (Davis, 2016; Jensen & Bang, 2013, Chapter 4 of this dissertation). Therefore, we measured identity as directly expressed in the members’ Twitter profile descriptions. We used members’ descriptions as they appeared on the first day of the selected time span (15 October 2014) in order to measure members’ identities before they engaged in the campaign. We employed the automatic classification tools (identity classifiers) developed in Chapter 4 to measure members’ salient identities (relational, occupational, and collective action-oriented). The classifiers use the profile description as an input and return a dichotomous outcome (1 = the classifier detects information about the type of social identity for which it has been trained; 0 = otherwise). In this way, we built three dichotomous variables (*relational identity*, *occupational identity*, and *collective action-oriented identity*) according to the results of the classifiers (1=yes). We assigned the value of 0 to the three variables when the member had no profile description. Identity types are not mutually exclusive. As social media foster the enactment of multiple identities (Davis, 2016), we found members scoring 1 in more than one type of identity.

Communication network position. We made use of Twitter data (tweets) to build the Movember campaign communication network from which we derived members’

communication network positions. As in Chapter 3, we used a Python script²⁰ to create a network matrix that considers members as nodes of the network and turns tweets into edges. There are four types of tweets: regular tweets, replies, mentions, and retweets. A regular tweet is a message sent by member A and does not generate any interaction; it results in a communicative edge that starts and ends with the same member. Replies, mentions, and retweets are texts representing communicative interactions as they include the “@username” and are thereby meant to address another user. A reply is member A’s direct answer to member B’s tweet. A mention happens when member A’s tweet explicitly refers to member B in order to draw his/her attention or alert him/her about something. A retweet is member A’s copy and rebroadcast of member B’s tweet. Thus, mentions, replies, and retweets are translated into directed edges linking the sender (A) to the recipient (B) of the message ($A \rightarrow B$). Edges are also weighted as a user might mention another user in multiple mentions, replies, or retweets. We imported the resulting communication network matrix in NetworkX,²¹ a Python package developed for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks (Hagberg, Schult, & Swart, 2018).

First, we used NetworkX to compute members’ harmonic centrality adapted to directed graphs as the sum of the reciprocal of the shortest path distances from all other nodes to u . We used the “harmonic_centrality” algorithm in NetworkX. The algorithm uses the following formula:

$$(1) \quad C(u) = \sum_{v \neq u} \frac{1}{d(v, u)}$$

where $d(v, u)$ is the shortest path distance between v and u . High values of harmonic centrality identify high centrality because a message takes a shorter path to travel from the sender to the recipient. The *harmonic centrality* variable ranges from 0 (low centrality) to 14 (high centrality). We log-transformed the variable to reduce skewness.

Second, we derived members’ core-periphery positions by calculating the *core number*, or *coreness*, of a node using the “core_number” algorithm (Batagelj & Zaversnik, 2003) in NetworkX. The *core number* of a node is the largest value k of a k -core containing that node. A k -core is a maximal subgraph of a network where all nodes have at least a degree of k (Seidman, 1983). The degree of a node is the number of in-linking (indegree) and out-linking (outdegree) connections that a node has with other nodes in the network. As the Movember campaign communication network is a directed graph, the degree k of a

²⁰ The code related to this script is available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

²¹ NetworkX is released under the 3-Clause BSD license (<http://networkx.github.io/>). The documentation file is available in Hagberg, Schult, & Swart (2018).

member is calculated by adding up the indegree and the outdegree. The *k*-core number is used to divide the network and, more specifically, each community in the network, into layers of cores. The highest *k* value identifies nodes located at the center of the network or of the community in a network. By decreasing *k*, detected nodes occupy positions that progressively move away from the core toward the periphery. We assigned a *k*-core number, or *coreness*, to each member according to the *k*-core a member belongs to. The *coreness* variable ranges from 1 (a member is on the periphery of a community) to 5 (a member is at the core). As network communities vary in size, we controlled for whether the community to which a member belongs is the biggest of the network (giant component). As *coreness* cannot be computed for isolated nodes, we assigned 0 to the *coreness* variable for all isolated members of the network. In interpreting the results, these members have a very peripheral position in the overall network (Burt, 2012).

Control variables. We used eight control variables. First, we controlled for movement members' sex (*Male* = 1), given that Movember is a men's health movement and the majority of its members are men (95%), and for differences between more and less experienced members by looking at the number of years of experience in the campaign (*Experience*). Second, we controlled for members' volume of Twitter activity (the variable *Tweets* is total number of tweets, mentions, replies, and retweets sent during the campaign) and the size of their social media audience (the variable *Followers* is number of followers they have on Twitter). Both variables were log-transformed to reduce skewness. Third, we controlled for the use of online and offline fundraising tactics. We built a dichotomous variable (*MoSpace URL*) to measure online external linking, which assesses whether members included URLs in their tweets to provide direct access to their personal pages on the Movember website (1 = yes). To control for offline fundraising tactics, we controlled for whether a member organized at least one event related to the campaign (*Event*, 1 = yes). Last, as the Movember Foundation encourages people to participate in the campaign by joining others and create a team, we controlled for whether a movement member participated in a team (*In Team*, 1 = yes) and whether a movement member was the leader of the team (*Team Captain*, 1 = yes).

Table 5.1 shows the means, standard deviations, and ranges of the dependent variable, independent variables, and controls (not log-transformed). Table 5.2 presents the bivariate correlations between the variables in the analysis. Owing to some high correlation values, we checked the variance inflation factor (VIF) of each of the predictors as an indicator of multicollinearity (Pan & Jackson, 2008). All VIF values were within the acceptable threshold, so no multicollinearity issue was detected.

Table 5.1. Descriptive statistics of variables (N=3,295).

Variable	Mean	Std. Dev.	Min.	Max.
Collected Donations (Total, \$)	340.70	1,523.10	0	60,946
Relational Identity (1 = yes)	0.26	0.44	0	1
Occupational Identity (1 = yes)	0.50	0.49	0	1
Action-oriented Identity (1 = yes)	0.22	0.42	0	1
Harmonic Centrality	0.08	0.61	0	14
Coreness	0.85	0.95	0	5
Male (1 = yes)	0.94	0.22	0	1
Experience	1.99	1.35	1	11
Tweets	4.54	8.59	1	161
Followers	3,590.06	73,913.72	0	3,864,591
MoSpace URL (1 = yes)	0.97	0.15	0	1
Event (1 = yes)	0.01	0.11	0	1
In Team (1 = yes)	0.78	0.41	0	1
Team Captain (1 = yes)	0.25	0.43	0	1

Sources: Twitter data obtained via a Twitter datagant on large online cancer awareness campaigns. Moreover data provided by the US Movember Foundation.

Table 5.2. Bivariate correlations between variables (N=3,295).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Collected Donations (ln)	1.00													
2 Relational Identity	0.01	1.00												
3 Occupational Identity	0.05**	0.40**	1.00											
4 Action-oriented Identity	0.01	0.33**	0.40**	1.00										
5 Harmonic Centrality (ln)	0.13**	0.05**	0.02	0.01	1.00									
6 Coreness	0.11**	0.05**	0.05**	0.04**	0.38**	1.00								
7 Male	0.13**	-0.00	0.00	0.01	0.02	-0.01	1.00							
8 Experience	0.20**	0.04**	0.05**	0.02	0.03	0.12**	0.10**	1.00						
9 Tweets (ln)	0.25**	0.08**	0.09**	0.07**	0.22**	0.50**	0.06**	0.17**	1.00					
10 Followers (ln)	0.09**	0.18**	0.32**	0.17**	0.23**	0.18**	0.03*	0.07**	0.24**	1.00				
11 MoSpace URL	0.050**	-0.01	-0.03*	-0.02	0.02	0.07**	0.02	-0.05**	0.05**	-0.09**	1.00			
12 Event	0.08**	-0.01	-0.01	0.00	0.02	0.11**	-0.01	0.11**	0.15**	-0.00	-0.01	1.00		
13 In Team	0.14**	-0.00	0.00	0.00	0.07**	0.08**	-0.03	0.04*	0.04**	0.04**	-0.00	0.03*	1.00	
14 Team Captain	0.18**	0.03	-0.00	-0.00	0.02	0.07**	0.03*	0.23**	0.15**	0.05**	-0.03	0.13**	0.30**	1.00

* = p<.05, ** = p<.01
Sources: Twitter data obtained via a Twitter datagant on large online cancer awareness campaigns. November data provided by the US Movember Foundation.

Table 5.3. Multivariate analyses using Tobit regression to explore the relation between online social identities, network positions, and collected donations during the 2014 US Movember campaign on Twitter (N=3,295).

Variables	Model 1 (Null)			Model 2 (Identity)			Model 3 (Network)			Model 4 (Full)		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
Relational Identity				-0.17	0.11	0.152				-0.19	0.11	0.108
Occupational Identity				0.22	0.11	0.045*				0.25	0.11	0.026*
Action-oriented Identity				-0.08	0.12	0.500				-0.06	0.12	0.593
Harmonic Centrality (ln)							1.17	0.24	0.000***	1.20	0.24	0.000***
Coreness							-0.24	0.06	0.000***	-0.24	0.06	0.000***
Male	1.51	0.33	0.000***	1.51	0.22	0.000***	1.44	0.22	0.000***	1.44	0.22	0.000***
Experience	0.27	0.03	0.000***	0.27	0.03	0.000***	0.28	0.03	0.000***	0.28	0.03	0.000***
Tweets (ln)	0.74	0.06	0.000***	0.74	0.06	0.000***	0.84	0.07	0.000***	0.84	0.07	0.000***
Followers (ln)	0.05	0.03	0.050	0.04	0.03	0.126	0.03	0.03	0.200	0.02	0.03	0.426
MoSpace URL	1.06	0.31	0.001**	1.07	0.31	0.001**	1.10	0.31	0.000***	1.11	0.31	0.000***
Event	0.47	0.43	0.271	0.47	0.43	0.269	0.54	0.42	0.202	0.54	0.42	0.201
In Team	0.81	0.12	0.000***	0.81	0.12	0.000***	0.80	0.12	0.000***	0.80	0.12	0.000***
Team Captain	0.49	0.11	0.000***	0.50	0.42	0.000***	0.49	0.11	0.000***	0.50	0.11	0.000***
Constant			-1.40			-1.40			-1.25			-1.25
Log Likelihood			-7090.48			-7087.99			-7075.63			-7072.62
Sigma			2.67			2.66			2.65			2.65

652 left-censored observations at Donations (ln) <= 0; 2,643 uncensored observations. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).
Sources: Twitter data obtained via a Twitter datagram on large online cancer awareness campaigns. November data provided by the US Movember Foundation.

5.4 Results

We conducted a multivariate analysis in Stata/IC 14.1 and used Tobit regression models (Tobin, 1958) because our dependent variable is left-censored (i.e., donations with a value of 0 all take on the value of such a threshold). Four regression models were estimated to test our five hypotheses (Table 5.3).

Model 1 is the baseline model with the dependent variable and control variables. Model 2 adds the identity variables to test H1a, H1b, and H1c. Only holding an online occupational identity has a positive and significant effect on the amount of collected donations, whereas we find no significant effects for the other identity types. Therefore, we can confirm only H1b. Next, Model 3 estimates the relation between network variables and collected donations to test H2a and H2b. In line with H2a, harmonic centrality is positively associated with the dependent variable: the higher the harmonic centrality of a member in the communication network, the higher the total amount of collected donations. Model 3 also shows that core-periphery positions have a significant and negative effect: the higher the coreness of a movement member in the communication network, the lower the total amount of collected donations. In other words, the closer a member is to the core of the communication network, the less they collect in donations. Thus, H2b is confirmed. Last, Model 4 combines Model 2 and Model 3 into a full model to determine whether the core findings of Model 2 are robust to the alternative explanatory measures presented in Model 3. In this full model, all independent variables maintain the same effects on the dependent variable.

Robustness checks.²² We conducted three robustness checks. First, the nature of our outcome variable (total amount of donations in US dollars) might cause a sample-selection bias because of the people who did not collect any donations. This potential bias was already addressed by using the Tobit model. However, as an additional check, we evaluated the effects of our independent variables on whether people made/received a donation (dichotomous outcome). Using the measure did not change the results regarding the effects of our two sets of independent variables. Similarly, we tested whether the success in collecting donations was related to the so-called “per-donor effect” for which the effect of a single donation by a single donor on fundraising success was greater than that of multiple donations by different donors (van de Rijt, Kang, Restivo, & Patil, 2014). When using the average amount of collected donations (total amount of money collected divided by the number of donations made/received) as dependent variable, the results regarding the effects of our two sets of independent variables did not change. Second, prior research

²² The results of the three robustness checks are provided in Appendix D at the end of this dissertation.

investigating the effect of the core-periphery position on individual performance has found curvilinear effects (Cattani & Ferriani, 2008; Dahlander & Frederiksen, 2011). We assessed this potential curvilinear effect on collected donations, but it was not significant. Last, as identity types were not mutually exclusive, we checked for the effect of having multiple salient overlapping identities on donations. The effect was not significant.

5.5 Discussion

In this paper, we answered the research question of how and why movements members' online social identity and communication network position influence the individual amount of collected donations during online health advocacy campaigns organized by SMOs. Using the 2014 US Movember health campaign on Twitter as an empirical context, we focused on the role of social identity as a motivator to engage in fundraising and of network position as a provider of opportunity structures to achieve successful outcomes.

First, we looked at three types of social identities that are typically salient online and found that only occupational identity had a significant and positive effect on the amount of collected donations, whereas there were no significant effects for relational identity and collective action-oriented identity. This result is insightful for SMOs, such as the Movember Foundation, as it shows that they can benefit from members who have an occupational identity to achieve successful outcomes in fundraising for social causes. In addition, in line with research investigating employee volunteering in social movements (Walker et al., 2011), our results show the importance of workplaces in volunteering and philanthropy. However, as our findings confirmed significant identity effects only for the occupational type, two questions merit future investigation. On the one hand, as occupational identity is a self-definition based on individuals' occupation, profession, career, or membership(s) of communities of practice, it has to be determined whether its positive association with donations might also be explained by the type of occupation or the level of education related to the person's profession or interest. On the other hand, while previous research supports the effectiveness of relational and collective action-oriented identities in predicting donation behavior (e.g., Shehu et al., 2015), we did not find any significant effects for these two identity types. This result can be explained by the fact that not all types of social identities might provide enough motivation for online action as it has been found in offline settings (see Chapter 4 of this dissertation). Future research should further investigate the extent to which online identities are proxies or partial representations of who an individual is in the real world.

Second, we focused on movement members' communication network position using centrality and core-periphery concepts from network theory. On the one hand, having

central positions in the communication process facilitated mobilization outcomes. Central movement members had high communication potential to reach out to many others in the network, and they were able to exploit this advantage to collect more donations than less central members. On the other hand, we found that being too close to the core of a communication network community constrained mobilization outcomes, which confirmed the backfire effect of core positions. Our findings showed that the higher the coreness of a member, the lower the amount of collected donations. Thus, the “strength of weak ties” of peripheral actors can be a more effective mechanism than the presence of strong ties in explaining successful online mobilization outcomes (Centola, 2010; Granovetter, 1973), such as fundraising.

5.6 Limitations and contributions

Our research has three limitations. First, owing to the focus on the Movember campaign on Twitter, this study’s generalizability is limited to the Twitter population and campaigns similar to Movember. Therefore, this study may suffer from selection bias, which is a typical issue in social movement and network research (Earl et al., 2014; Lewis et al., 2014). Future research could test our hypotheses by using other types of advocacy campaigns and social media platforms.

Second, we looked at the relationship between social identity and donations as unidirectional because we considered identity preceding and determining a consequent action. Nevertheless, identity theory addresses a bidirectional relationship between social identity and action because identity might change over time after action is taken (Davis, 2016). Future research could investigate whether people’s online social identity might vary over time during the campaign and develop hypotheses of bidirectional relationships between identity and mobilization outcomes. In addition, more research is needed to “triangulate” online and offline identities in order to deepen our understanding of the “consistency between online and offline identity claims” in the study of human actions (Davis, 2014, p. 6).

Third, we did not consider any longitudinal effect of individual centrality and core-periphery positions on collected donations. Previous research argues that longitudinal work is important to assess the impact of social media in shaping people’s experiences in networked collective action (González-Bailón & Wang, 2016; Rohlinger & Bunnage, 2015). Future research could investigate how changes in the communication network position over time might affect online mobilization outcomes.

Despite its limitations, our research offers four contributions. First, we contribute to social movement research by investigating the micro-mobilization mechanisms under

which SMOs' campaigns are effective (see Chapter 1 of dissertation). We showed that movement members' online salient social identities and communication network positions are factors that can explain how and why people successfully achieve outcomes that require a substantial effort and can benefit SMOs' causes. In this way, we also answered calls for the adoption of an integrative approach using identity and networks to advance our understanding of online micro-mobilization dynamics (see Chapter 2 of this dissertation) and for more research on the appropriate network concepts to assess pivotal actors in online mobilization (González-Bailón & Wang, 2016, see Chapter 3 of this dissertation).

Second, we contribute to media and communication research by showing the potential of social media as platforms for communication and interaction with and support for meaningful action in our contemporary digitally mediated society. We show that social media provide platforms for "communication repertoires" (Mattoni & Treré, 2014), and communication can play an important role in fostering charitable responses and collective action.

Third, this work provides insights for research on health fundraising and philanthropy by showing the relevance of fundraising campaigns in social media. As studies usually investigate donors' behavior, we deepen our understanding of the dynamics at play on the fundraisers' side and of the psycho-social mechanisms that drive people's voluntary engagement to collect money for medical research via social media. In this regard, we contribute to calls for more research that uses social media data in health research (Centola & van de Rijt, 2015; Gruebner et al., 2017) and in the study of pro-social behavior (Boulianne et al., 2018).

Fourth, we show the potential of mixed-methods and computational approaches for social sciences to deal with the complexity of large datasets derived from social media (see Chapter 2 of this dissertation). By using automatic classifiers, network analysis, and statistical analysis, we show that the adoption of a multidisciplinary approach not only serves a data triangulation function to create robust measures of the theoretical concepts (Bail, Brown, & Mann, 2017) but can also provide social scientists with input to revisit traditional social theory, which is often strongly consolidated in offline settings (see Chapter 4 of this dissertation).

Chapter 6

The Effect of Framing Adoption and Emotions on Individual Mobilization Outcomes during a Health-related Online Social Movement Campaign

This is a single-author chapter.

Abstract

Social movement research has long been part of studying how framing processes and emotional involvement influence participation in collective action. However, little is known about how these micro-level mechanisms affect individual mobilization outcomes in online social movement campaigns. In this study, I first explore how social movement organizations' framing, through the use of language, symbols, and slogans, characterizes movement members' discourse in social media and the extent to which the movement's dominant framing becomes hegemonic during online mobilization. Then, I investigate how movement members' adoption of the movement's dominant framing in the online discourse and their level of emotional involvement in the framing process influence individual fundraising outcomes during a health-related campaign on Twitter. By combining automated text analysis, the use of a plagiarism detector, network visualizations, and regression analysis, I find that almost one-third of the discourse that movement members generated on Twitter during the campaign aligns with the Movember Foundation's dominant framing. However, the more movement members use the movement's language, slogans, and frames in their tweets, the less they collected in donations. By contrast, the use of emotional language in framing processes was positively associated with the amount collected in donations. In this way, I show the importance of the authenticity of communication and emotions as important micro-mobilization dynamics related to individual participation in online social movement campaigns. This study contributes to research on social movements, media, and communication.

6.1 Introduction

Social movement organizations (SMOs) attempt to effect social change by mobilizing various target groups, including individual adherents. To this end, SMOs appeal to people's interpretations of the world (Gamson, 1988; Snow et al., 1986) and their emotional involvement (Aminzade & McAdam, 2002; Goodwin, Jasper, & Polletta, 2004; Rao, 2009) to encourage individual participation in collective action, such as advocacy campaigns. For example, SMOs seeking to raise awareness of cancer detection and prevention define – or *frame* – cancer as one of the most dramatic problems our society is facing and appeal to people's orientations, values, and emotions to motivate healthy behavior and support medical research through fundraising activities.

Social movement research has long been part of studying how framing processes and emotional involvement resulting from interactive communication influence participation in collective action (for reviews, see e.g., Bail, 2012, 2016; Cornelissen & Werner, 2014; Polletta & Ho, 2006; Vasi et al., 2015). However, this stream of research has three main shortcomings. First, the research has primarily investigated how SMOs align their orientations, interests, and values with those of potential individual adherents in order to foster recruitment and mobilization (frame alignment and frame resonance, see e.g., Benford & Snow, 2000; Snow & Benford, 1988; Snow et al., 1986). Research following this approach has been criticized for being “movement-centric” (Walder, 2009), putting emphasis on the strategic, “top-down” use of framing in social movements (Oliver & Johnston, 2000), and having lost sight of the more interactive, bottom-up processes happening across movements' individual adherents or members (for reviews, see Cornelissen & Werner, 2014; Polletta & Ho, 2006, Chapter 1 of this dissertation). In fact, individuals participating in social movements are important actors who contribute to framing formation, extension, and transformation enacted via interactive communication processes occurring in mobilization (Benford & Snow, 2000; Cornelissen & Werner, 2014; Kaplan, 2008; Polletta, 2006; Polletta & Ho, 2006). On the one hand, framing theories assume that when movements' adherents embrace the dominant frame, they are more likely to commit to action because the adoption of movements' dominant frames produces solidarity and engagement (Benford & Snow, 2000). On the other hand, framing theories have as yet failed to investigate whether deviating, at least to some extent, from the dominant frame (that is, being more authentic in framing messages) produces better outcomes. This is an important omission because the authenticity of communication as a driving force of individual participation in collective action can deepen our understanding of social movement organizations and outcomes (Luna, 2017; Polletta, 1998, 2006; Snow, Benford, McCammon, Hewitt, & Fitzgerald, 2014; Snow & Moss, 2014; Walker & Stepick, 2018; Wooten, 2010).

Second, research investigating the role of emotions in social movements has found that appealing to people's emotions is a driving factor of collective action (e.g., Aminzade & McAdam, 2002; Bail, 2012; Bail et al., 2017; Flam, 2015; Goodwin et al., 2004; Rao, 2009; Ruiz-Junco, 2013; Starr, 2017; Summers-Effler, 2010; van Stekelenburg & Klandermans, 2013; Volpi & Jasper, 2018). In this line of research, scholars focus on the role of language as a means to *frame* situations and express emotions (Bail et al., 2017; Flam, 2015; Snow et al., 2014; Thomas et al., 2009; van Stekelenburg & Klandermans, 2013) that trigger "worthiness, unity, numbers, and commitment" to action (Tilly, 1994, 1999, 2003, 2004). However, most of these studies focus on the movement level and analyze macro-trends across organizations and over time while failing to investigate the use of emotional language and frame alignment across individual actors within movements (Snow et al., 2014). Little is known about how movements' adherents or members channel emotions by using language to mobilize and how such individual appeals to emotions affect individual participation and outcomes in social movements.

Third, previous research has studied how SMOs exploit media outlets to frame processes and organize collective action (e.g., Andrews & Caren, 2010; Bail, 2012; Hara & Estrada, 2005; Hara & Huang, 2011; Vasi et al., 2015). These opportunities have multiplied with the advent of social media, such as Twitter, that provide movements and individuals with open platforms to engage directly in communication, negotiate meanings, and express emotions (Bail, 2012; Bennett & Segerberg, 2012; Hara & Huang, 2011; Tufekci & Wilson, 2012, Chapter 1, Chapter 3 and Chapter 5 of this dissertation). Scholars find that social media facilitate discursive opportunities that have direct effects on mobilization outcomes (Bail, 2016; Vasi et al., 2015). Yet, little is known about how social media provide arenas that facilitate (or constrain) interactive communication micro-processes, framing processes, and movement outcomes.

Addressing these three shortcomings is important to understand the micro-level mobilization mechanisms that explain the effectiveness of online social movement campaigns. In this chapter, I seek answers to two research questions. First, I explore how SMOs' framing, in the form of language, symbols, and slogans, characterizes the movement members' discourse in social media and the extent to which the movement's dominant framing becomes hegemonic during online mobilization. Hence, the first research question in this chapter is:

Question 6.1: How does the dominant framing of social movement organizations characterize movement members' discourse in social media during campaigns?

Second, I take a micro-level perspective and investigate the mechanisms (namely framing processes and appeals to emotion) that occur in communication processes during mobilization, as well as their effects on individual mobilization outcomes during social movement campaigns. In particular, I focus on the individual level of movement adherents whom I consider to be SMO members. I investigate the extent to which both a) the adoption of the movement's dominant framing and b) the level of emotional involvement in the framing process affect individual fundraising outcomes during a health-related campaign. I look at these processes in social media because the latter provide both new opportunities to study individual-level mobilization dynamics and large data sources for sociological research. The second research question is:

Question 6.2: To what extent do a) movement members' adoption of the movement's dominant framing and b) the level of emotional involvement in members' framing processes affect movement members' fundraising outcomes during online campaigns?

In this chapter, I undertake an analysis of the Movember Foundation and its campaign to raise awareness of prostate and testicular cancer prevention and early-detection behavior. The foundation organizes annual campaigns to promote conversations around men's health and collect donations for medical research. The foundation allows people to become official members of the movement organization by registering online, and it encourages the use of social media as a tool to organize and communicate action. This particular setting provides an ideal case to analyze online micro-level mobilization dynamics that are relevant to movement members' mobilization. Using the case of the US 2014 campaign on Twitter, I first look at how the Movember Foundation's framing characterizes the movement members' discourse on Twitter during the campaign and the extent to which the movement's language, symbols, and slogans are hegemonic at the micro-level of individual adherents (Question 6.1). In this light, I combine automated text analysis techniques, plagiarism detection, and network visualizations to detect the extent to which the Movember Foundation's framing characterizes the movement members' discourse on Twitter during the campaign. Second, I use regression models to explain the effects of movement members' framing adoption and their use of emotional language in framing on the individual amount of donations collected for medical research during the campaign (Question 6.2).

The rest of the chapter is structured as follows. First, I describe the case study's background and highlight its value in addressing the chapter's research questions. Second, I develop hypotheses with respect to this study's objectives. Third, I describe the rich online data, methods, and techniques used and report the results of the investigation. Last,

I discuss the theoretical and methodological contributions for research found at the intersection of social movements, media, and communication.

6.2 “Grow a Mo, save a Bro”: the case of the Movember Foundation

Australia, 2003. Two friends in a bar are discussing how fancy the moustache is. They challenge each other to grow a moustache for a year to see whether they will be able to turn it into a new trend. After some time, they meet again and realize that, while growing a moustache is fun, they have piqued the interest of a large number of people curious about their unusual hair. Thus, the two friends decide to use the symbol of the moustache to promote conversation for good. Inspired by the women of the Pink Ribbon breast cancer movement, they initiate a men’s health movement called Movember, a name meant to evoke the “mo” of the moustache. Soon after, the Movember Foundation is born as a charity organization whose goal is to promote men’s health around the world (Movember, 2014). Within a few years, it turns into a global movement and organization thanks to word of mouth, community building, and digital media.

Every November, the foundation organizes campaigns worldwide to raise awareness, promote conversation around prostate and testicular cancer prevention and early-detection behavior, and collect donations for medical research and men’s health programs. It uses symbols (e.g., growing a moustache) and poses challenges (e.g., doing sports every day) to make people identify with the cause during the campaign. In addition, the foundation encourages campaign participants to become official members by registering as *MoBros* and *MoSistas* on its website. Since 2003, the Movember Foundation has registered 4,746,905 official members, who have raised about 580 million Australian dollars to fund over 800 men’s health programs around the world (Movember, 2014).

The peculiar characteristics of the Movember Foundation make it an ideal case to investigate the objectives of the present study. According to the foundation’s official records, Movember is considered a global grassroots movement whose goal is health advocacy (Movember, 2014). Its primary aim is to change the idea that discussing men’s health is a problem. In social movement framing terms, the Movember Foundation is clear about its intention to develop its “collective action frame” (Benford & Snow, 2000) to inspire and legitimize its activities and campaign. The foundation defines (diagnoses) as problematic the fact that prostate and testicular cancers have generally been obscured by a “culture of silence” that poses social, psychological, and structural barriers preventing men from seeking out health services (Jacobson, 2010, p. 87). A potential solution (prognosis) to this problem is to empower men to focus on health in *manly* ways. Thereby, the moustache becomes a symbol of masculinity and a motivational driver to engage men

more fully about their health and well-being (Jacobson, 2010). In the words of Goffman (1959), growing a moustache can be regarded as a “performance” that embodies confidence and strength and enriches men’s status as citizens caring about their own health and contributing to a good public cause (Wassersug et al., 2015).

The Movember Foundation widely uses framing strategies to empower men to live healthy lives and care about their health. It designs *ad hoc* messages promoting the use of a particular language, symbols (i.e., the moustache), and slogans (e.g., “Change the face of men’s health” or “The power of the Mo”). However, the foundation clearly expresses the constructive and collaborative nature of the campaign: It claims to use a bottom-up approach by encouraging personal narratives and storytelling as key mechanisms to contribute to the cause and foster support (Movember, 2014). In so doing, it encourages both offline and online mobilization. On the one hand, it invites people to take their action to the street, organize events to meet locally, and engage in face-to-face conversation. On the other hand, it uses social media to promote its campaign, spread the message, and encourage people’s active participation not only in fundraising but also in sharing their own stories. In the words of the foundation,

“Movember is a word of mouth campaign driven by in-person communication and reinforced through digital and social media. Movember is about telling stories. It’s about each Mo Bro and Mo Sista embracing the cause and then choosing to share their personal participation story in a way that is meaningful to them.” (Movember, 2014, p. 69)

6.3 Theory and hypotheses

In social movement research, the study of framing processes as factors explaining support for and participation in social movement organizations (SMOs) develops as a reaction to the disregard for social psychological approaches to collective action by resource mobilization theory (Gamson, 1988; Snow & Benford, 1988; Snow et al., 1986). The concept of a frame is derived from the work of Goffman (1974, p. 11) and defined as “principles of organization which govern the subjective meanings we assign to social events.” Collective action frames are “action-oriented sets of beliefs and meanings that inspire and legitimate the activities and campaigns of a social movement organization” (Benford & Snow, 2000, p. 614). In other words, they are interpretative packages that SMOs use to mobilize potential adherents or members (Polletta & Ho, 2006). SMOs define, or frame, certain events or situations as ones that are in need of change and provide people with meaning and interpretation to motivate and foster support and action for a collective common interest (Benford & Snow, 2000; Gamson, 1988; Snow & Benford, 1988; Snow et al., 1986).

Movements produce collective action frames through acts of framing, that is, by using symbolic language and cognitive meaning to perform three “core-framing tasks” (Benford & Snow, 2000, p. 615): a) diagnosis – defining problems, for example, recognizing that little attention is given to men’s health, even as many men are dying from cancer; 2) prognosis – proposing solutions to the problem, for example, empowering men to care about their health and collect donations for men’s health programs; and 3) motivations – engaging in collective action, for example, by promoting calls to action to participate in men’s health advocacy campaigns and using symbols like the moustache. An important precondition for these framing processes to succeed in mobilizing movement members is “frame alignment,” namely, “the linkage of individual and SMO interpretive orientations, such that some set of individual interests, values and beliefs and SMO activities, goals, and ideology are congruent and complementary” (Snow et al., 1986, p. 464). It is not only a question of strategically and coherently performing these tasks by providing a compelling set of arguments that makes a movement effective (Polletta & Ho, 2006) but also the ability to make frames resonate, that is, producing frames that fit with people’s view of the world around them (Gamson, 2004; Polletta, 2008). In this way, people participating in social movements contribute to framing processes (Benford & Snow, 2000; Cornelissen & Werner, 2014; Kaplan, 2008; Polletta, 2006; Polletta & Ho, 2006). They do so through interactive communication occurring in mobilization, where they create and negotiate meanings from which organized action follows (Cornelissen, Mantere, & Vaara, 2014; Cornelissen & Werner, 2014; Donnellon, Gray, & Bougon, 1986; Kaplan, 2008). Movement members not only embrace the movement’s dominant frame (Benford & Snow, 2000) but also reframe, reinvent, and improvise definitions, language, and symbols (Luna, 2017; Polletta, 2006; Rao, 2009; Snow & Moss, 2014).

Research into social movements and framing has found that individuals’ adoption of movements’ dominant framing shows adherence to the cause and fosters commitment, solidarity, the forming of a collective identity, networking relationships, and connections, all of which are preconditions for centralized mobilization (Polletta, 1998, 2006; Snow & Benford, 1988). When individuals adopt the movement’s dominant framing in the form of language, symbols, slogans in their speech, texts, or discourse (Romanos, 2015), which is what Movember members do when they use framing like “Change the face of men’s health” in their tweets, the expectation is that these people will act in line with the logic of the movement’s frame. If they do that, it is also expected that they might be more likely to participate in and contribute to the social movement (Benford & Snow, 2000; Oliver & Johnston, 2000). This expectation finds its empirical evidence in recent studies on framing and communication in social media, such as Facebook and Twitter, during collective action (e.g., Chan, 2016; Gerbaudo, 2015; Hara & Huang, 2011; Pickerill, 2009). In fact, SMOs

use social media to promote framing processes (Ackland & O'Neil, 2011; Choi & Park, 2014; Hara & Huang, 2011; Harlow, 2012; McCaughey & Ayers, 2003; Pickerill, 2009), draw people's attention to their cause (Bail, 2016), and create discursive opportunities for collective action (Bail, 2016; Vasi et al., 2015).

Although individuals' use of a movement's language, symbols, and slogans might satisfy essential preconditions of adherence, support, and participation in mobilization, some scholars find that the adoption of the movement's dominant frame does not always produce the expected outcome of triggering support. For example, Polletta (2006) finds that, although the US student protests against racial segregation in the 1960s adopted the "dominant injustice frame" (Benford & Snow, 2000), the use of such a frame only had an indirect effect on the large mobilization outcome that followed. Massive mobilization was triggered by the use of a new frame, which emerged from individual students' discourse and proposed spontaneity of action instead of injustice. As a matter of fact, spontaneity, namely "events, happenings, and lines of action, both verbal and nonverbal, which were not planned, intended, prearranged, or organized in advance of their occurrence," is often considered an important mechanism determining collective action outcomes (Ho, 2018; Snow & Moss, 2014, p. 1123). Similarly, movements' framing can benefit from interactive processes with movement members, who can extend and transform the framing spectrum in a bottom-up approach (Benford & Snow, 2000; Luna, 2017; Polletta, 2006; Rao, 2009; Snow & Moss, 2014). Scholars argue that *authentic* experiences foster deeper, more meaningful engagement and operate as driving forces in mobilization (Luna, 2017; Polletta, 1998, 2006; Roy, 2010). Similar dynamics can be found during campaigns and protests in the social media context. The openness of social media allows individuals to contribute to collective action framing in more personalized ways (Bennett, 2003; Bennett & Segerberg, 2012; Hara & Huang, 2011; Milan, 2015; Papacharissi, 2010). Media scholars find that social media foster the production of more authentic action frames, which are the result of self-motivating and personal expressive content that fosters individual participation outcomes (Benkler, 2006; Bennett & Segerberg, 2012). In this vein, I posit that movement members' adoption of dominant frames might have a counterproductive effect on individual participation outcomes, such as fundraising. In the case of health campaigns aiming to collect donations for medical research and programs, if movement members use the same messages and stay too close to the movement's line, there is a risk that their discourse will become dry and uninteresting to their audiences and potential donors, thus attracting less in donations. More specifically:

Hypothesis 1: In online, health-related social movement campaigns, the more movement members adopt the movement's dominant framing in their discourse, the lower the amount of collected donations will be.

Another aspect related to framing and social movements pertains to the role of emotions in mobilization processes (e.g., Aminzade & McAdam, 2002; Bail, 2012; Bail et al., 2017; Flam, 2015; Goodwin et al., 2004; Jasper, 2011; Rao, 2009; Ruiz-Junco, 2013; Starr, 2017; Summers-Effler, 2010; van Stekelenburg & Klandermans, 2013; Volpi & Jasper, 2018). Emotions trigger “worthiness, unity, and commitment” (Tilly, 1994, 1999, 2003, 2004) and can predict an individual’s willingness to take part in collective action (Jasper, 2011; Leach, Iyer, & Pedersen, 2006; Starr, 2017; van Stekelenburg & Klandermans, 2013; van Zomeren, Leach, & Spears, 2012). These effects hold for both positive emotions, such as joy, and negative emotions, such as fear or anger (Bail et al., 2017; Starr, 2017). Together, framing processes eliciting emotions promote energy and enthusiasm, which are likely to make activism exciting and to strengthen collective identity (Ho, 2018; Jasper, 2011; Polletta, 1998, 2006; Snow et al., 2014; Snow & Moss, 2014; Starr, 2017; Walker & Stepick, 2018). Evidence of the motivational potential of emotions in triggering social movement outcomes is also found in online mobilization contexts (Bennett & Segerberg, 2012; Starr, 2017). In this vein, I posit that during health fundraising campaigns, when movement members use language that appeals to people’s emotions, they might be able to attract and motivate others to a larger extent, thus resulting in higher collected donations.

Hypothesis 2: In online, health-related social movement campaigns, the more movement members display emotions in their discourse, the higher the amount of collected donations will be.

6.4 Research design

The analysis is divided into two stages. First, I look at how the Movember movement’s framing characterizes movement members’ discourse on Twitter during the campaign and the extent to which the language, symbols, and slogans of the movement become hegemonic at the micro-level of individual members (Question 6.1). Second, I investigate the effects of movement members’ framing (HP1) and their display of emotions in framing via language (HP2) on individual mobilization outcomes in social movement campaigns (Question 6.2).

As an empirical context, I use the US 2014 Movember campaign on Twitter, which aimed to raise awareness about prostate and testicular cancer prevention and early-detection behavior. For both sets of analysis, I used data from two sources. First, I obtained Twitter data, such as users’ Twitter activity and profile information, via a Twitter datagrant on large online cancer awareness campaigns, including Movember. The datagrant consists of archival data (2008–2014) of more than 300 million tweets related to

nine campaigns for six different types of cancer (see Introduction, see Section 1.5). Second, I obtained Movember US data, including movement members' IDs, amount of collected donations, years of experience in the campaign, and gender, from the US Movember Foundation. Based on the work of Nguyen et al. (2015), I merged the data from these two sources using a list of matched profiles of US users ($N = 3,295$) who were officially registered on the Movember website and had a Twitter account linked to their Movember profile at the time of the campaign.²³ These users represent the population of this study. The selected time frame for both the Twitter and the Movember data begins two weeks before the start of the campaign (15 October 2014) and finishes two weeks after the end of the campaign (15 December 2014). During this period, 14,970 tweets were sent by 3,295 Movember members, who collected 1,122,613 US dollars in donations.

6.5 Detecting and analyzing the Movember Foundation's framing in movement members' discourse on Twitter during the US 2014 campaign

In the first stage of the analysis, I explore how the Movember Foundation's framing characterizes movement members' discourse on Twitter. I do this by examining the extent to which the language and slogans promoted by the movement become hegemonic at the micro-level of individual members' Twitter activity (Question 6.1). To this end, I adopted a novel approach that combines manual content analysis, the use of a plagiarism detector software, and network component analysis.

First, I analyzed the content of the Movember Foundation's annual report (Movember, 2014), the foundation's website,²⁴ and the tweets sent from the @MovemberUS Twitter account²⁵ to identify how the foundation frames its mission and goals and promotes its campaign. In this way, I was able to identify a set of recurring words and statements with a specific function, such as slogans used to motivate participation or address the campaign's goals, as well as texts about health-related topics (Table 6.1). It was also possible to identify an association between words and statements with the diagnosis, prognosis, and motivational "core-framing tasks" identified by Benford and Snow (2000, p. 615). For example, the series of health #MoChats promoted by the foundation can be interpreted as a diagnostic core-framing task because they refer to men's health problems and, thus, indicate the forming of diagnostic frames. Statements like *Change the face of men's health* and *Help me beat prostate/testicular cancer* are considered prognostic frames because they discuss potential solutions for men's health. Last, slogans using the *power of the moustache*

²³ More information on the Twitter data collection and preparation are provided in Appendix B at the end of this dissertation.

²⁴ Website pages consulted: <https://us.movember.com> and <https://us.movember.com/news/7293/grow-your-mo-team>.

²⁵ Tweets sent by @MovemberUS are part of the Twitter datagrant project (see the Introduction, Section 1.5).

and *made in Movember* and calling for team participation highlight symbolic identification and collective participation, thus providing a motivational framing.

Then, I looked at the content of the tweets ($N = 14,970$) sent by the Movember members in order to detect whether and how much the tweets are characterized by the use of language, words, or statements related to the foundation's dominant framing. Owing to the large number of tweets sent during the campaign, identifying and counting statements within the corpus of tweets via hand coding was not feasible. Therefore, I combined automated preprocessing techniques with plagiarism detection and network component analysis to facilitate this procedure. This novel approach progressively reduced the number of tweets in the corpus by detecting and aggregating identical or very similar tweets (Figure 6.1). To start with, text preprocessing and data cleaning were required to facilitate the identification of unique statements (i.e., identical portions of text) in the tweets (*Step 1a*, Fig. 6.1). All the tweets, identified by a *TweetID* number, were preprocessed to remove URLs, punctuation, and all typical Twitter features included in the texts, such as RT, mentions, and hashtags.²⁶ Two percent of the tweets ($N = 208$) were blank after the preprocessing operation, meaning that these tweets were comprised exclusively of the deleted features (e.g., *Tweet 13* in Fig. 6.1). This small portion of tweets was the first group of those identified as authentic and unique texts – in other words, without any relation to Movember's framing.

Next, I removed the duplicates from the corpus of cleaned tweets ($N = 14,702$) by using the Stata 14.0 software (*Step 1b*, Fig. 6.1). This software recognizes identical data by reporting and tagging the duplicates in the dataset. In this way, I deleted the tweets that were tagged as duplicates and obtained 10,402 unique statements, to each of which I assigned a *StatementID* number. If a tweet did not have a duplicate, it counted as a unique statement (e.g., *Tweet 9* and *Tweet 12* in Fig. 6.1). In the corpus, there were 9,765 unique statements – in other words, 9,765 unique tweets. There were 637 statements with duplicates, such as *Statements 1, 2, 3, and 5* in Fig. 6.1, totaling 4,937 tweets. The high number of duplicates shows that the overall discourse on Twitter is characterized by a certain degree of mechanically reproducing content, which is a common feature of the Twitter platform, as users can “retweet” and rebroadcast a tweet with the click of a button.

²⁶ The code related to this script is available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

Table 6.1. Movember Foundation framing: recurring words and statements, the sources where this data was retrieved, and the associated functions.

Recurring Words and Statements Used by the Movember Foundation	Source	Function	Core-framing Task
Change the face of men's health	Annual report; website, tweets	Slogan	Prognostic
Donate to my/our hairy efforts			
Help/Please make a donation; by making a donation	Annual report; website, tweets	Issue a challenge: make a donation	Prognostic
Thank you XX for donating	Annual report; website	Say thank you	-
Made in Movember	Annual report; tweets	Slogan	Motivational
Help (me/us) beat prostate/testicular cancer	Annual report; website	Slogan	Prognostic
1 in 7 men will be diagnosed with prostate cancer in their lifetime	Tweets	Health Mochats: discussing health issues	Diagnostic
1 in 4 adults will experience a mental health problem this year			
About 8820 cases of testicular cancer will be diagnosed in 2014			
Testicular cancer is the most common cancer in (young) men			
Movember's here and I'm looking for new Mo Bros and Mo Sistas for my team	Annual report; website	Get social; join/create a team	Motivational
Power of the moustache / Power of the Mo	Annual report; website, tweets	Issue a challenge: grow moustache: symbolic identifier	Motivational
Help (me/us) raise awareness	Annual report; website, tweets	Raise awareness	Motivational
We are in this together	Annual report; website	Slogan	Motivational

Figure 6.1. Mixed-method approach to detect similar vs unique tweets in the corpus (N = 14,970): combination of automatic content analysis, plagiarism detection, and network component analysis.

Table 6.2. Most frequent statements in the Movember members’ corpus of tweets (N=27).

StatementID	Text	Tweets	Related to the Movement’s Framing?
1	Im changing the face of mens health by supporting Support my journey by making a donation	782	Yes
2	Help me to change the face of mens health this by making a donation to my moustache	725	Yes
3	Donate to my hairy efforts and help beat prostate cancer here	320	Yes
4	Movemberers here and Im looking for new Mo Bros and Mo Sistas for my team	265	Yes
5	1 in 4 adults will experience a mental health problem this year Im taking action with	172	Yes
6	About 8820 cases of testicular cancer will be diagnosed in 2014 Donate to change this	156	Yes
7	Join me by signing up at and changing the face of mens health this	98	Yes
8	Im a Mo Sista helping change the face of mens health Join me by making a donation	77	Yes
9	Im changing the face of mens health with Movember join me and support the Mo	75	Yes
10	PLZ Donate to my hairy efforts and help beat prostate cancer here	54	Yes
11	Im trying to prove to my US coworkers that Canadians can grow mustaches Can you help me w a	47	No
12	Hey Im trying to prove to my US coworkers that Canadians can grow mustaches Can you help me w a	31	No
13	This Movember Im changing the face of mens health and I want you to stay healthy so check out this health tip	31	Yes
14	match my for	28	No
15	Were in this together Sign up for Movember to change the face of mens health	28	Yes
16	Thank you for donating to Together we are changing the face of mens health	27	Yes
17	Im changing the face of mens health with Movember Check this out	26	Yes
18	A smooth start to w a smooth whiskey Join us as we pair cocktails	25	No
19	This Im raising awareness and funds for testicular cancer and mens health join me	24	Yes
20	Im helping change the face of mens health with my donation Join me in supporting this important cause	22	Yes
21	Movemberers arrived and awesome looking moustaches like this one are sprouting to change the face of mens health	19	Yes
22	Look whos part of the Movember movement and changing the face of mens health	17	Yes
23	Im changing the face of mens health with Movember join me and support the	14	Yes
24	Movember the annual month long moustache growing marathon is kicking off around the world	14	No
25	Donate to my efforts and help beat prostate cancer here	13	Yes
26	Follow the rules of Sign up shave down and grow a moustache for mens health	13	Yes
27	Its at Honest Shop now Every RETWEET thru 1121 1 Honest will donate too	13	No

Then, I calculated the frequency of the tweets in each statement in order to assess the most frequent statements in the corpus and conduct a more in-depth content analysis to detect whether the language of the movement becomes hegemonic in the tweets²⁷ (Table 6.2). I found that the most frequent statements (N=27) consisted of similar, recurring portions of text (such as “*changing the face of men’s health*,” “*help beat prostate cancer*,” or “*support me by making a donation*”) that were linked to the Movember Foundation’s framing, as identified in Table 6.1. For example, the two most frequent statements were “*Im changing the face of mens health by supporting Support my journey by making a donation*” (N= 782) and “*Help me to change the face of mens health this by making a donation to my moustache*” (N=725). Although these statements were not identical, they were framed using the similar strings of text: *changing the face of mens health; change the face of mens health; by making a donation*. The two most frequent statements made up 10% of the total amount of tweets sent during the campaign. A recurring set of words related to the dominant framing of the Movember Foundation was also identified in other frequent statements, as Table 6.2 shows.

Owing to the high similarity in content between the most frequent statements, it was important to assess the extent to which such similarity extends to the whole corpus of tweets. I used the concept of plagiarism to detect whether the tweets that the movement members sent were characterized by the use of the same words and whether such words and statements were related to the movement’s dominant framing. In addition, the plagiarism analysis reveals how strings of words are combined in the same tweet and shows how movement members adopt and adapt the dominant framing. For these purposes, I employed the plagiarism detection software WCopyfind²⁸ (Step 2a, Fig. 6.1). WCopyfind compares the statements and identifies exact matches of text. The software detects matches on the basis of two parameters: The Shortest Phrase to Match (SPM) indicates the minimum number of words to consider a match, whereas the Fewest Matches to Report (FMR) is the fewest matching words in the statements that are reported by the software. For this analysis, I set the SPM to 4 as statements are very short texts and 4 is the minimum suggested to have reliable results. In this way, the software ignores matches of three words or fewer. I set the FMR to 9 as 9 is the average number of words in the statements and it was found to be the optimal parameter to detect a sufficient level of plagiarism (similarity) in the statements that was simply related to a few matched words.²⁹

²⁷ The most frequent statements were identified by using a cutoff value (12) calculated as the sum of the mean and standard deviation of all *Statements ID* frequencies.

²⁸ WCopyfind is free software developed by Bloomfield (2011). WCopyfind has already been used in computational sociology to analyze large amounts of text and found to be reliable to assess similarity between texts (Bail, Brown, & Mann, 2017).

²⁹ I chose 9 as the FMR parameter because smaller values reported more but shorter matches, whereas bigger values reported too few results. The limitation of such a relatively high FMR is that WCopyfind does not report matches resulting from parsing strings of fewer than nine words. Therefore, if matches are found and reported by the software for the string “1 in

According to these two parameters, WCopyfind parsed all statements into nine-word strings and then identified all cases where four of the nine words in a string matched. These matches were reported in a web browser output (HTML) that showed the exact match between two statements. WCopyfind detected 23,516 exact matches in 1,055 of the 10,402 of the statements in the corpus.

To easily identify how statements were matched by sharing identical texts, I used network component analysis and visualizations in Gephi 0.9.2 software (*Step 2b*, Fig. 6.1). More specifically, I converted the output of the plagiarism detector to a relational matrix that was used to create an undirected graph. In the graph, each statement is a node, and an exact match between two statements is an edge that links the two statements, as shown in Figure 6.2. I imported the relational matrix in Gephi and obtained a network of 1,055 nodes (i.e., the statements for which WCopyfind detected a match) and 23,516 edges (i.e., number of detected matches in the 1,055 statements). Then, I used Tarjan's (1972) algorithm to identify the (weakly) connected components of the graph as groups of statements linked together by exactly the same matches.

For example, the statements

- a) *1 in 7 men will be diagnosed with prostate cancer in their lifetime Donate to help change the face of mens health*
- b) *Help me to change the face of mens health this and donate to my monstache*
- c) *Join my team and help change the face of mens health Raise money for mens health research and forego*
- d) *Join my team help make a difference 1 in 7 men affected by prostate cancer in their lifetime*

are part of the same component because they are all linked by exact matches of words, such as *prostate cancer in their lifetime* (a and d), *change the face of mens health* (a, b, and c), and *Join my team* (c and d). I consider these statements to be very similar to each other because they are built around the same strings of words. Therefore, the components can be seen as groups of statements (and tweets) having the same semantic meaning.

Tarjan's algorithm identified 169 components that altogether aggregate 4,325 tweets. Additional tweets ($N = 359$) were manually added to the components to account for spelling errors and unreported matches due to the parameter used in the plagiarism detection³⁰ (*Step 3c*, Fig. 6.1). Overall, 4,684 tweets (31% of the total number of tweets)

2 men will be diagnosed with cancer," strings like "1 in 2 men are diagnosed with cancer" are not reported by the software. Similarly, spelling errors are not taken into account by the plagiarism detector. To overcome these limitations, I combined the use of the plagiarism detector with a manual search of strings of words in the corpus of tweets of the matches reported by the software. A guideline for the manual search is available in Appendix E at the end of this dissertation.

³⁰ See previous footnote.

were found to be identical or very similar to each other. This means that almost one-third of the Twitter activity generated by the movement members during the campaign is framed around the same words and contents. Figure 6.2 shows the biggest detected components (N = 5). Table 6.3 reports the list of exact matches detected by the plagiarism detector and the manual annotation in each of the biggest components. Again, the matched words of the biggest components were found to be mostly related to the Movember movement's dominant framing. For example, *Component 3* is the biggest component of the network and contains 2,384 tweets. These tweets make up 16% of the total number of tweets sent during the campaign, and they all contain strings such as '*Change the face of men's health*,' '*by making a donation*,' and '*beat prostate testicular cancer*.' These strings of text are also often combined with typical health-related tweets promoted by the foundation, such as *1 in 7 men will be diagnosed with prostate cancer* and *About 8820 cases of testicular cancer will be diagnosed in 2014*. In *Component 17*, variations of '*Change the face of men's health*' are combined with "*We are in this together*" and '*thank you*.' The second-biggest component, *Component 15*, includes 462 tweets (3%) mentioning '*donate to my (hairy) effort*' and '*help beat prostate cancer*.' The third-biggest component, *Component 20*, addresses the call for team participation, another important element of the Movember Foundation's framing. Together, the biggest components cover 24% of all the tweets (N = 3,587) sent by movement members during the campaign. This shows a certain degree of hegemony in the language promoted by the Movember Foundation in the Twitter discourse generated by movement members during the campaign.

Figure 6.2. Biggest components of the Undirected Network of Matched Statement (N = 5).

In the network, each node represents a statement, whereas edges stand for a matching of statements. Nodes have different colors according to the component they belong to. The biggest components, which are identified with their ComponentID number, are the ones that aggregate the highest amounts of tweets (cutoff value = 190).

Table 6.3. Biggest components (C) of the Undirected Network of Matched Statements: distributions of tweets (T) and matched strings in the component.

C	T	Matches in the Component
3	2,384 (16.0%)	1 in 2 men will be diagnosed with cancer in their lifetime
		1 in 7 men will be diagnosed with prostate cancer (in their lifetime)
		a donation to my moustache
		beat prostate testicular cancer
		by making a donation (to my moustache)
		change/changing the face of men's health (by supporting)
		help (me/us) raise/raising awareness
		help change the face of men's health this by making a donation
		help me change the face of men's health
		help me to change the face of men's health this by donating
15	462 (3.1%)	help us change the face of mens health this by making a donation to
		I'm a Mo Sista helping change the face of mens health
		I'm growing a my mustache
		In 2014 more than 233000 men will be diagnosed with prostate cancer
		join my team and help
		My moustache is in need of your support Please donate
		please donate to my
		Sign up for Movember to change the face of
		support my journey by making a
		support to my/our (hairy) effort(s)
20	305 (2.0%)	Testicular cancer is the most common cancer in (young) men
		the face of men's health
		use the power of the moustache (mustache)
		will be diagnosed with cancer
		donate to my efforts and help beat prostate cancer here
		donate to my/our (hairy) effort(s)
		help (me/us) beat prostate cancer
		Movember's here and I'm looking for new Mo Bros and Mo Sistas for my team
		for donating this and helping me changing the face of men's health
		Thank you XX for donating
17	242 (1.6%)	Thank you XX for donating to Together we are changing
		together we are changing the face of men's health
		we are in this together
		1 in 4 adults will experience a mental health problem this year
		1 in 4 adults will experience a mental health problem this year Take action and join my team
		1 in 4 adults will experience a mental health problem this year Im taking action with join me
		3,587 (24.0%)
61	194 (1.3%)	

C = ComponentID; T = Tweets (sum of the number of tweets in the component and the number of manually annotated tweets; and percentage of the total number of tweets). The biggest components are the ones that aggregate the highest amounts of tweets (cutoff value = 190).

6.6 Investigating the effects of movement members' framing adoption and the use of emotional language in framing on the individual amounts of donations collected during the campaign

Having established that movement members' online discourse is in part characterized by the Movember movement's dominant framing, I now turn to evaluating HP1 and HP2 regarding the effects of framing adoption and emotional language in framing on the individual amounts of donations collected for medical research during the Movember campaign.

6.6.1 Measures

Dependent variable: individual amount of collected donations

The Movember Foundation aims to improve men's cancer prevention and early-detection behavior and promote social change in public perceptions regarding men's health. To achieve these goals, the foundation encourages fundraising for medical research. In this analysis, I focus on movement members' collection of donations as a fundraising and support activity contributing to the social movement (Andrews, Ganz, Baggetta, Han, & Lim, 2010). Collecting donations is an active form of participation that requires a financial contribution involving some risk and effort (Van Laer & Van Aelst, 2010; Walker, 2008). Research shows that social media provide a platform where SMOs can easily mobilize people to collect money by soliciting small-scale but collectively-of-impact forms of support that often require a simple click (Garrett, 2006). Thus, this study's outcome variable is the total amount of donations in US dollars collected by a movement member during the campaign (from 15 October to 15 December 2014) via online sources. The donation amount is derived from both members' personal donations to the Movember Foundation and other people donating to the member in support of his/her efforts for the campaign. People can make a donation to the members via their personal pages on the Movember website. By the end of the specific period, 19.79% of the members had not collected any donations during the campaign. The *Donations* variable ranges from 0 to 60,946 US dollars. I log-transformed the variable to reduce skewness (Zumel & Mount, 2014) and added a small constant (+1) to handle the cases where the *Donations* variable was equal to 0.

Adoption of the movement's dominant framing in the Twitter discourse

This study's first independent variable (*Movember Framed Tweets*) measures the adoption of the Movember movement's dominant framing by movement members in the Twitter discourse. As a result of the plagiarism detection analysis (Section 6.5), I was able to identify strings of words that were closely related to the dominant framing proposed by

the Movember Foundation. I used the list of such strings to search for tweets aligned with the movement's dominant framing.³¹ Then, I calculated the total number of those tweets that contained such strings and were sent by a movement member during the campaign. I log-transformed the variable *Movember Framed Tweets* to reduce skewness (Zumel and Mount, 2014). I used the natural logarithm and added a small constant (+1) to handle the cases where the *Movember Framed Tweets* variable was equal to 0. Altogether, 27% of the total number of tweets sent during the campaign period contained at least one of the identified strings related to the movement's dominant framing; 60% of the movement members sent at least one of those tweets.

Display of emotions in the Twitter discourse

In line with social movement literature investigating the role of emotions in mobilization (for a review, see Bail et al., 2017, among others), I derived members' emotional involvement from the style of language used in the tweets. To this end, I conducted an automated text analysis using Linguistic Inquiry and Word Count (LIWC) (Tausczik & Pennebaker, 2010). Originally from the fields of language studies and social psychology, this software is increasingly being used in sociology, social psychology, and media research (see e.g., Bail et al., 2017; He, Glas, Kosinski, Stillwell, & Veldkamp, 2014; Joyce & Kraut, 2006; Kovács, Carroll, & Lehman, 2017; Smith et al., 2015; Walther, Deandrea, & Tong, 2010). LIWC is dictionary-based, that is, it counts and assigns words to categories according to a predefined list of words.³² LIWC identifies content words (e.g., nouns, verbs), as well as style and function words related to social and psychological states, such as anger and affection. I used this tool to identify the frequency of words in the tweets that were associated with emotions. LIWC has a particular category that relates to emotional words and is called "Affect." It includes words related to both positive and negative emotions: *Thank you so much for supporting #Movember and the #DrewManChu! I encourage you to keep supporting charity* is a tweet with high positive emotions, whereas *Day 9, family over initial shock, still complaining bitterly #movember* expresses more negative emotions. Although LIWC already does some text preprocessing, such as lowercasing, removing capitalization, and sentence structure (tokenization), it is not customized for Twitter text data. Therefore, some additional preprocessing was needed to remove HTML formats,

³¹ For the list of strings used in the search, see Appendix E at the end of this dissertation (Table E1).

³² Although LIWC has been broadly applied to social science research, it is not free from imperfections; these are mainly due to its dictionary-based approach to automatic content analysis. This is one of the limitations common to all automatic tools like LIWC, in particular when they are applied to short texts, like tweets or Facebook posts (for a discussion on the issue, see e.g., He, Glas, Kosinski, Stillwell, & Veldkamp, 2014). Although I tried to reduce the errors by manually double-checking the results returned by LIWC, other more refined tools using machine learning could be used in future testing to improve the performance and outcomes of this type of analysis. To this end, I conducted the same analysis with two other sentiment classifiers, AFINN (Nielsen, 2011) and Vader (Hutto & Gilbert, 2014), but I did not obtain better results. In addition, both AFINN and VADER text classification results were highly correlated with the ones obtained using LIWC.

hashtags (#), and mentions (@) from the tweets and to convert Unicode text into readable symbols.³³ Next, I used the cleaned tweets as input for LIWC, which returned the results for each tweet as a percentage of words related to emotions. Then, I aggregated the results at the individual level by calculating the median of the frequency of emotional words of all tweets sent by a Movember member. Last, I log-transformed the variable (*Emotional words*) to reduce skewness.

Control variables

Individual characteristics. I controlled for movement members' sex (*Male* = 1) because Movember is a men's health movement and the presence of men among the movement members far outweighs that of the women: Almost 95% of the members are male. Social movement studies often address sex to control for differences between men and women in the level of participation (for a review, see Caren, Ghoshal, and Ribas 2011, among others). Scholars find differences between men and women in health advocacy outcomes (Best, 2012; Jacobson & Mascaro, 2016), cancer activism (Himmelboim & Han, 2014; Kedrowski & Sarow, 2010), and, more generally, in the use of social media in the public sphere (Polletta & Chen, 2013). Addressing such differences is also important to account for variations in the use of language (Tausczik & Pennebaker, 2010).

Next, I controlled for members' years of experience on the campaign (*Experience*) because more experienced members might differ from less experienced ones in collecting donations, in the adoption of SMO's framing, and in the ability to exploit social media platforms for activism due to the knowledge they acquired in previous years of participation. Being experienced members might signal a better understanding of the cause and more expertise and knowledge about the campaign and its missions, and it might symbolize a high sense of commitment and collective identity (Jacobson & Mascaro, 2016, see Chapter 3 of this dissertation). Studies show that active and longstanding members' engagement within SMOs can also improve organizational capacity and the effective achievement of social movement outcomes (Andrews et al., 2010). Data from the Movember members' profiles was used to calculate their experience, as members indicated in which year it was that they participated in the campaign for the first time. The *Experience* variable ranges from 1 (a member registered in 2014) to 11 years.

Individual online activity, tactics, and social media audience. The volume of Twitter chatter is a common control variable adopted in studies of online mobilization (see Vasi et al., 2015) as it represents one of the most direct ways to measure discursive

³³ The code related to this script is available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

opportunities. Although the use of this control variable is legitimate, I excluded it from the models due to multicollinearity issues with the key variable *Movember Framed Tweets* and some of the other controls (*Retweets*, *Mospace URLs*, and *Social Media URLs*). By contrast, I used the number of retweets sent by movement members (*Retweets*) to control for the possible bias of the use of retweets as “mechanical actions” (Milan, 2015). *Retweets* was log-transformed due to skewedness.

Social media like Twitter offer a variety of ways to express and disseminate content in ways other than through text. For example, studies show that images and videos increase the attention people pay to the content of messages and frames (Bail et al., 2017; Vasi et al., 2015) and contribute to the construction of collective identities (for a review, see Chapter 2 of this dissertation). Furthermore, previous research has found that the use of URLs or hyperlinking, as a way to provide direct access to external online resources, not only increases message diffusion (Velde, Meijer, & Homburg, 2015) and individuals’ online influence (Johnson et al., 2015), but is also instrumental in collective action (Jacobson & Mascaro, 2016; Pilny & Shumate, 2012). External linking is quite widespread on Twitter as it allows users to extend their discourse beyond the platform’s 140-character tweet length.³⁴ In fact, 99% of Movember members included URLs in their tweets. Therefore, I conducted an explorative URL analysis to control for the type of external linking that members adopt as a tactic that might influence the collection of donations. First, I retrieved all the URLs contained in each member’s tweets, removed the ones that were no longer active, and extracted the original source for all shortened URLs (by default, Twitter makes long URLs more compact to use less characters).³⁵ In this way, I obtained 12,660 active URLs, which were included in 78.88% of the tweets sent during the campaign. Next, I stripped out ‘www’, ‘http,’ and all extensions (e.g., .com; .org) to identify similar and identical domains and then counted their distributions to identify the most frequent types of URLs. 73.11% of the links had a Movember domain (e.g., *movember.com*; *mospace.com*), followed by 12.28% *instagram.com* links and 3.53% *facebook.com* links. Other URLs linked to YouTube videos or other photo- or video-based social media (e.g., Pinterest, Vimeo, Vine), websites (e.g., Tumblr), or photo repositories. I divided the external links into three categories: Movember-related URLs, social media URLs (i.e., Facebook, Instagram, Klou, LinkedIn, Twitter), and photo/video URLs (i.e., Tumblr, Vimeo, Vine, YouTube, Pinterest, and photo repositories). I counted the number of each type of URL per tweet and aggregated the data at the individual level. Next, I created three variables (*Mospace URLs*, *Social Media URLs*, and *Photo and Video URLs*) by determining the

³⁴ In 2017, the maximum amount of characters permitted in a single tweet was increased to 280.

³⁵ The code related to this script is available in the GitHub repository related to this dissertation. For a repository guideline, see Appendix F at the end of this dissertation.

proportion of each URL type in the tweets sent by a member and calculated the natural logarithm to reduce skewedness.

Last, I controlled for the number of followers (*Followers*) as a measure of social media audience and the potential reach of tweets, framing, and external linking. People on Twitter with large audiences might have both higher chances to have their tweets read and more potential online donors. In addition, the presence of a large audience can also point to the presence of celebrities or very well-known people who might be more successful in attracting others' attention. As there are only a few people with a high number of followers (variable ranges between 0 and 3,864,591), the distribution of the *Followers* variable is skewed: For this reason, natural-log transformation of this variable was necessary.

Individual offline tactics. Although the focus of this chapter is online mobilization dynamics, SMOs encourage people to take the cause to the street. The Movember Foundation, for example, inspires people to take action and organize events to meet face to face, create conversations, promote health activities, and collect donations. I controlled for whether Movember members organized an event during the campaign because events can be seen as activation strategies to engage others to support the cause (Walker, 2008), as well as tactics to draw attention to the cause (Bail et al., 2017). In addition, being active in organizing events might signal a certain degree of participation effectiveness that can prove valuable for social movement outcomes (Andrews & Caren, 2010). The Movember Foundation allows its members to create and sponsor events via a dedicated registration page on the Movember website. There are three types of events that can be hosted. First, *Shave Events* are usually planned at the beginning of the campaign month when men shave their face before growing a new moustache. These events can be regarded as tools for recruitment and to give motivation to participate because they emphasize the collective dimension of participation (*let's shave together*) and contribute to the construction of the campaign's identifier (i.e., the moustache). Second, *Move Events*, which occur anytime during the campaign month, use the physical challenge to motivate people to participate. It offers a way to promote health and to give people the motivation to donate, and it involves a sense of commitment to the cause by engaging people in sports activities, which require a certain amount of (physical) effort. Third, *Party Events* are the most frequent. They occur anytime and are often organized as social moments to promote awareness and fundraising. I obtained event data at the individual level from the Movember Foundation and created three dichotomous variables (*Shave Events*, *Move Events*, *Party Events*), one for each type of event, where a value of 1 indicates that members organized at least one such event during the campaign.

Team participation to control for external opportunity structures. Social movement literature emphasizes the need to consider various levels of analysis when investigating the factors facilitating mobilization processes (Cress & Snow, 2000; Della Porta & Diani, 2006; Edwards & McCarthy, 2004; King, 2008; Vasi et al., 2015), as well as framing processes (Benford & Snow, 2000). I controlled for member participation in teams providing external opportunity structures (van den Broek, Walker, Ehrenhard, Priante, & Need, 2017; Walker & Stepick, 2014) and facilitating (or constraining) fundraising. The Movember Foundation, for example, encourages collective participation (“*Don’t Mo alone*”) and motivates people to create or join “*Mo Teams*,” which are considered to be *ad hoc* transitory groups of people that are characterized by temporality and short-term goals (Andrews et al., 2010; van den Broek et al., 2017). I used three variables to control for team participation. First, I created the variable *In Team* to assess whether a member belongs to a team (1 = yes). Second, I controlled for *Team Leader* (yes = 1) as a measure of whether an individual is the leader of a team, because leadership is positively associated with successful fundraising associated with SMOs and the ability to coordinate collective action (e.g., Andrews et al., 2010), social influence, public opinion, identification, and communication processes (Ashforth & Mael, 1989; Bail et al., 2017; Johnson et al., 2015). Last, I controlled for whether a person belongs to a team with other members on Twitter (*Other Members on Twitter*; yes = 1) because the presence of other teammates on the same social media platform might influence the extent to which a person puts effort into online contributions (in terms of both engagement and framing) because being part of a team with other members on Twitter can produce what is called the *free rider effect* (Olson, 1968). Research into online mobilization shows that free-riding is quite common on social media as unmotivated people can abstain from a substantial contribution while still benefiting from the common goal due to the easy and low-cost ways of participating online (Barberá et al., 2015; Lewis et al., 2014).

Table 6.4 shows the means, standard deviations, and ranges of the dependent variable, independent variables, and controls (not log-transformed). Table 6.5 presents the bivariate correlations between the variables in the analysis.

Table 6.4. Descriptive statistics of variables (N=3,295).

Variable	Mean	Std. Dev.	Min	Max
Donations (Total, \$)	340.70	1523.10	0	60,946
November Framed Tweets	1.22	2.23	0	66
Emotional words (median)	3.70	4.49	0	25
Male (1 = yes)	0.94	0.22	0	1
Experience	1.99	1.35	1	11
Retweets	0.62	2.93	0	65
Mospace URLs	2.80	4.93	0	115
Social Media URLs	0.61	2.46	0	53
Photo & Video URLs	0.08	0.79	0	28
Followers	3,590.06	73,913.72	0	3,864,591
Shave Events (1 = yes)	0.00	0.04	0	1
Move Events (1 = yes)	0.00	0.04	0	1
Party Events (1 = yes)	0.01	0.10	0	1
In Team (1 = yes)	0.78	0.41	0	1
Team Leader (1 = yes)	0.25	0.43	0	1
Other Members on Twitter (1 = yes)	2.14	4.53	0	33

Sources: Twitter data obtained via a Twitter datagram on large online cancer awareness campaigns, November data provided by the US Movember Foundation.

Table 6.5. Bivariate correlations between variables (N=3,295).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Donations (ln)	1.00														
2 Movement Framed Tweets (ln)	-0.03*	1.00													
3 Emotional words (ln)	0.09**	0.00	1.00												
4 Male	0.13**	-0.01	-0.07**	1.00											
5 Experience	0.20**	0.04*	0.02	0.10**	1.00										
6 Retweets (ln)	0.09**	0.17**	0.00	0.02	0.16**	1.00									
7 Mospace URLs (ln)	0.24**	0.53**	0.05**	0.05**	0.11**	0.37**	1.00								
8 Social Media URLs (ln)	0.12**	0.03*	-0.02	0.06**	0.11**	0.27**	0.27**	1.00							
9 Photo & Video URLs (ln)	0.08**	0.07**	0.03	0.01	0.07**	0.43**	0.24**	0.17**	1.00						
10 Followers (ln)	0.09**	-0.06**	0.07**	0.03*	0.07**	0.08**	0.11**	0.14**	0.09	1.00					
11 Shave Events	0.03*	0.06**	-0.00	0.01	0.03*	0.18**	0.09**	0.08**	0.13	-0.00	1.00				
12 Move Events	0.03	0.03*	0.01	0.01	0.07**	0.07	0.03*	0.03	0.01	0.01	0.33**	1.00			
13 Party Events	0.07**	0.06**	-0.00	-0.01	0.10**	0.21**	0.10**	0.11**	0.11	-0.01	0.27**	0.13**	1.00		
14 In Team	0.14**	0.03	-0.00	-0.03	0.04*	0.05**	0.04*	0.01	0.01	0.04**	0.02	0.00	0.03*	1.00	
15 Team Leader	0.18**	0.10**	-0.01	0.03*	0.23**	0.06**	0.14**	0.10**	0.05**	0.05**	0.04*	0.04*	0.12**	0.30**	1.00
16 Other Members on Twitter	-0.09**	0.00	0.00	-0.24**	-0.07**	0.00	-0.00	-0.02	-0.01	0.02	-0.00	-0.01	-0.02	-0.24**	-0.10**

* = p<.05, ** = p<.01

Sources: Twitter data obtained via a Twitter datagant on large online cancer awareness campaigns. Movement data provided by the US Movement Foundation.

Table 6.6. Multivariate analysis using Tobit regression to investigate the effects that adopting the movement dominant framing and the display of emotions have on donations (N=3,295).

Variables	Model 1			Model 2			Model 3			Model 4		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
November Framed Tweets (ln)				-1.12	0.10	0.000***				-1.11	0.10	0.000***
Emotional words (ln)							0.22	0.04	0.000***	0.20	0.04	0.001**
Male (1 = yes)	1.24	0.22	0.000***	1.13	0.22	0.000***	1.32	0.22	0.000***	1.21	0.22	0.000***
Experience	0.29	0.03	0.000***	0.28	0.03	0.000***	0.28	0.03	0.000***	0.27	0.03	0.000***
Retweets (ln)	-0.05	0.01	0.003**	-0.05	0.01	0.003**	-0.05	0.01	0.004**	-0.05	0.01	0.003*
Mospace URLs (ln)	0.98	0.08	0.000***	1.59	0.10	0.000***	0.96	0.08	0.000***	1.56	0.10	0.000***
Social Media URLs (ln)	0.16	0.09	0.072	0.04	0.09	0.617	0.17	0.09	0.041*	0.06	0.09	0.459
Photo & Video URLs (ln)	0.35	0.25	0.169	0.22	0.25	0.361	0.32	0.25	0.204	0.20	0.25	0.415
Followers (ln)	0.09	0.02	0.001**	0.04	0.02	0.089	0.08	0.02	0.005**	0.030	0.02	0.172
Shave Events (1 = yes)	-0.18	1.20	0.876	-0.04	1.17	0.972	-0.11	1.19	0.922	0.02	1.17	0.984
Move Event (1 = yes)	0.51	1.15	0.657	0.82	1.13	0.469	0.41	1.15	0.717	0.72	1.12	0.520
Party Events (1 = yes)	0.70	0.48	0.144	0.77	0.47	0.101	0.71	0.48	0.139	0.77	0.47	0.098
In Team (1 = yes)	1.06	0.12	0.000***	1.05	0.12	0.000***	1.06	0.12	0.000***	1.05	0.12	0.000***
Team Leader (1 = yes)	0.31	0.11	0.007**	0.76	0.11	0.001**	0.33	0.11	0.005**	0.39	0.11	0.001**
Other Members on Twitter	-0.07	0.01	0.000***	-0.07	0.01	0.000***	-0.07	0.01	0.000***	-0.07	0.01	0.000***
Constant		-0.35			0.03			-0.57			-0.18	
Log Likelihood		-7068.07			-7006.20			-7055.87			-6995.05	
Sigma		2.65			2.60			2.64			2.59	

652 left-censored observations at Donations (ln) <= 0; 2,643 uncensored observations. * p<0.05; ** p<0.01; *** p<0.001.
Sources: Twitter data obtained via a Twitter idatagant on large online cancer awareness campaigns. Movement data provided by the US Movement Foundation.

6.6.2 Estimation techniques

In order to test Hypothesis 1 and Hypothesis 2, I conducted a multivariate analysis in Stata/IC 14.1 using a Tobit regression model (Tobin, 1958) as the dependent variable (*Donations*) is left-censored (i.e., all donations with a value at 0 take on the value of such a threshold). Four regression models were estimated to test the hypotheses. Model 1 is the baseline model with the amount of collected donations and control variables. In Model 2, I added the variable measuring the adoption of the movement's dominant framing to test HP1. Model 3 includes the variable related to the display of emotional words in tweets to test HP2. Model 4 combines the two independent variables into a full model.

6.6.3 Results

Table 6.6 shows the results of the models that estimate the effects that adopting the movement's dominant framing and the display of emotions have on collected donations. Model 2 indicates the adoption of the movement's dominant framing has a negative effect on the amount of collected donations, holding all controls constant. Overall, this result shows that the more movement members use language, slogans, and statements from the movement in their tweets, the less they collect in donations. Thus, Hypothesis 1 is confirmed. Model 3, instead, shows that the use of emotional language in tweets has a (small but) positive and significant effect on collected donations. Therefore, Hypothesis 2 is confirmed.

Results in Table 6.6 also show differences in collected donations between men and women in favor of more donations for men, probably because Movember is a men's health movement. Experience on the campaign is also positively associated with donations. Regarding online and offline tactics, the effect of retweets is negative and significant, which probably suggests that the mechanical reproduction involved in retweeting does not promote the collection of donations. Instead, external linking to Movember pages has a positive effect on donations, which shows how movement members might exploit Twitter as a means to direct potential donors to their fundraising page and channel their audience's attention toward the foundation's official webpage. By contrast, the organization of offline events results is not significantly associated with the amount of collected donations. This result might suggest that offline mobilization may not be as effective a predictor of donations as online tactics and framing. This can be explained by the fact that only a small portion of movement members organized events during the campaign. The size of the audience in terms of Twitter followers is only significantly associated with collected donations in Model 1 and Model 3. Finally, results concerning team participation show that external (team) opportunity structures foster and constrain online mobilization. On the one hand, being in a team and being a team leader foster success in collecting donations. On the other hand, the presence of other teammates on Twitter is negatively

associated with donations. This negative effect might be associated with the *free-rider* effect (Olson, 1968).

Model 4 combines Model 2 and Model 3 to determine whether the core findings from Model 2 are robust to the alternative explanatory measure presented in Model 3. In this full model, the adoption of SMOs' framing continues to have a negative and significant association with donations, with slightly different effect size in the various indicators. The use of emotional words is still positive and significant.

6.7 Discussion and conclusion

In this chapter, I answered two research questions. First, I explored how the Movember Foundation's framing characterizes movement members' discourse on Twitter and the extent to which the movement's language, symbols, and slogans is hegemonic at the micro-level of the movement members during online mobilization (Question 6.1). By adopting a novel method combining automated text analysis techniques, the use of a plagiarism detector, and network visualizations, I found that almost one-third of the Twitter discourse generated by movement members during the campaign aligned with the Movember Foundation's dominant framing. In particular, 60% of the members sent out at least one tweet containing slogans or statements belonging to the dominant framing. This shows that movement members aligned with the dominant framing at least to some extent. This might have been facilitated by the Twitter platform, which is known for allowing an easy reproduction of contents via its retweet function. In this respect, previous research had found that social media such as Twitter are effective at promoting framing processes (Ackland & O'Neil, 2011; Choi & Park, 2014; Harlow, 2012; McCaughey & Ayers, 2003; Pickerill, 2009) and creating discursive opportunities for collective action (Bail, 2016; Vasi et al., 2015).

Second, I investigated how the adoption of the movement's dominant framing by movement members and the level of emotional involvement in members' framing processes during mobilization affect individual fundraising outcomes during the campaign (Question 6.2). Although the majority of movement members adopted the Movember Foundation's dominant framing to some extent, the more members used the movement's language, slogans, and statements in their tweets, the less they collected in donations. In other words, the more they adopted the dominant framing in the online discourse, the less good their fundraising performance was. This outcome might be explained by the fact that when movement members stay too close to the movement's line, the online discourse might become dry and uninteresting, thus derailing others' participation and involvement, as in the case of fundraising for health issues. A growing body of work highlights how pivotal authenticity and spontaneity of action are in collective action because they provide

people with energy and enthusiasm, which makes activism more likely (Ho, 2018; Luna, 2017; Polletta, 1998, 2006; Roy, 2010; Snow & Moss, 2014, p. 1123), in particular in grassroots mobilization (Walker & Stepick, 2018). Authenticity is a socially constructed attribute according to which an actor or practice is considered more real and genuine than principles and ideologies (Carroll & Wheaton, 2009; Goldberg, Hannan, & Kovács, 2016; Hsu, Koçak, & Hannan, 2009; Lehman, Kovács, & Carroll, 2014; Negro, Koçak, & Hsu, 2010; Walker & Stepick, 2018) and can deal with conformity and originality (Fine, 2004; Peterson, 1997). Authenticity is seen as a means for framing (Luna, 2017) and provides a more meaningful (authentic) and human connection (Luna, 2017; Polletta, 2006; Walker & Stepick, 2018). In this vein, I argue that communication that advances the broader meta-level of the movement's dominant framing but does not repeat exactly the same talking points can be more effective because it appears to be more authentic. Therefore, when movement members deviate in modest ways from the dominant message, they might obtain better outcomes than when they adopt the dominant framing. Future research could investigate this proposition by looking in more depth at the actual content of successful, authentic framing. Research in this direction might prove particularly fertile if focused on social media as they facilitate the production of more authentic frames (Benkler, 2006; Bennett & Segerberg, 2012; Hara & Huang, 2011). Some studies show that online activism, such as tweeting, liking a page on Facebook, or using a banner in a profile is a form of "slacktivism," that is, low-cost low-risk participation that does not produce substantial social change (Morozov, 2009) or actual contributions to the cause (Karpf, 2012; Lewis et al., 2014). By contrast, this study shows that movement members' framing processes in social media might go beyond the "mechanic reproduction" (Milan, 2015) of the dominant framing, and, by appearing more authentic, movement members can exert the power of triggering action.

In addition, this study makes clear the importance of displaying emotions in framing processing occurring during online mobilization. In line with previous research, I found that the more movement members used emotional language in their tweets, the more they collected in donations. Some studies show that emotional discourses create an opportunity structure in which SMOs stimulate the engagement of the target groups (Bail, 2012; Bail et al., 2017; Goodwin et al., 2004; Rao, 2009; Schrock, Holden, & Reid, 2004; Snow et al., 2014; Snow & Moss, 2014; Starr, 2017). Here, I find that much happens at the individual level of movement members, who channel emotions via the use of language in framing processes and obtain important support from others in achieving mobilization outcomes, such as donations for medical research. Future research could investigate the difference between negative and positive emotional words in framing, for which I did not find significant effects when treating them separately, and use methods other than dictionary-based approaches to infer emotions from the use of language.

Taken together, these findings offer three important contributions. First, this study contributes to social movement research by showing the importance of investigating the individual-level dynamics of framing processes during collective action. People who adhere to social movements are important actors who contribute to framing processes via interactive communication occurring in mobilization (Benford & Snow, 2000; Cornelissen & Werner, 2014; Kaplan, 2008; Polletta, 2006; Polletta & Ho, 2006, Chapter 1, Chapter 3 and Chapter 5 of this dissertation). This study contributes to a growing body of social movement research on the role of authenticity in collective action and social movement organizations (e.g., Luna, 2017; Polletta, 1998, 2006; Snow & Moss, 2014; Walker & Stepick, 2018). By showing that movement members' adoption of the movement's dominant framing is less effective in individual mobilization outcomes, such as collective donations for a social cause, this study advances our understanding of the authenticity of communication and framing as an important micro-dynamic of collective action and a driving force of individual participation and, more broadly, of social movement organizations' outcomes. Studies of other types of social movement campaigns waged online (not limited to the health domain) could also provide useful insights to deepen our understanding of the role of authenticity and emotional involvement in other mobilization contexts and advance research on how SMOs generate awareness and social change. By studying how the Movember Foundation's framing characterizes its members' discourse on Twitter during the annual campaign, this study broadens our understanding of how SMOs use social media to stimulate the discourse online and their broader consequences on mobilization individual outcomes, such as fundraising (see Chapter 1, Chapter 3 and Chapter 5 of this dissertation). In this way, I show the practical implication of Twitter activism for social movement organizations and provide valuable findings for activist practices. Future research should extend the study of micro-level mobilization dynamics on other social media platforms beyond Twitter in order to generalize this study's findings to the broader online context.

Second, this study contributes to media and communication research by providing new evidence on the role of social media in shaping new landscapes for social movements and micro-mobilization dynamics. Media research, in fact, has mostly focused on the role of technological artifacts and communication technologies and not much on framing processes and emotional narratives that are peculiar to the social media landscape (Bennett & Segerberg, 2012; Bennett & Toft, 2010; Hara & Huang, 2011). Results from this study, in line with Chapter 3 and Chapter 5, show that social media provide arenas that facilitate interactive and communication processes across movement members.

Last, this study has important methodological contribution for the use of computational approaches in social sciences. The adopted strategy combines automated

text analysis techniques with novel methods (such as the use of a plagiarism detector), more conventional network analysis, and statistical methods. Thereby, I show the potential of mixed-method approaches for social sciences to deal with the complexity of large datasets from social media.

Chapter 7

Summary and Conclusions

Few studies have assessed the effectiveness of online social movement campaigns in generating meaningful social change – that is, translating online action into meaningful (offline) action. This dissertation examined how effective online social movement campaigns are by investigating the micro-mobilization dynamics relevant to individual participation. The research question of this dissertation was:

How and why do micro-mobilization dynamics explain the effectiveness of online social movement campaigns in achieving social change?

In this chapter, I summarize the main findings of the research based on the sub-questions presented in the Introduction (Section 7.1), before presenting an overview of the dissertation's theoretical, methodological, and practical contributions (Section 7.2), a discussion of its limitations (Section 7.3), and an outline of future research directions (Section 7.4).

7.1 Answering the research questions: summary of the key findings³⁶

This dissertation examined four key micro-mobilization dynamics defined as the micro-structural and social-psychological dimensions and related processes that play a role in mobilizing movement members (see Introduction, Section 1.4): identity, networks, framing, and emotions.

Chapter 2 provided a systematic literature review of identity and collective action via computer-mediated communication (CMC) by answering the following questions:

Question 2.1: Which concepts, methodological approaches, and perspectives are used in the literature on identity and collective action via computer-mediated communication?

Question 2.2: What are the main findings from the literature on the role of identity in collective action and computer-mediated communication's impact on identity processes?

By reviewing 59 empirical studies published from 2012 to 2016, we found that empirical research on identity, collective action, and CMC is broad and diverse because of contributions from multiple disciplines, theoretical perspectives, and methodological approaches. Findings from the literature show that identity drives collective action. More

³⁶ As explained in the Introduction (footnote 2), on the whole, this dissertation uses a first-person perspective. In this section, the pronoun "we" is used to emphasize the collaborative effort that went into particular parts of the research (see Chapter 2, Chapter 4 and Chapter 5).

specifically, the studies that were reviewed investigate the role of social identity in new forms of collective action and the factors influencing the role of identity in collective action. In addition, the studies show that CMC might support or constrain identity processes during online mobilization. Given the shortcomings in the findings, we derived five recommendations for future research directions:

1. Conduct more empirical studies that take a multi-level approach to studying identity. Chapter 3 of this dissertation examined collective identity; Chapter 4 and Chapter 5 focused on social identity.
2. Investigate identity as a dynamic process that evolves over time. Chapter 3 studied the formation and evolution of collective identity in online mobilization.
3. Shed more light on the role of communication technologies in identity processes. Chapter 4 illustrated how an online social identity can be assessed based on how people describe themselves in social media.
4. Examine the conditions and intervening factors (such as media use or networks) that, together with identity, can explain mobilization outcomes. This dissertation examined the role of networks and identity in Chapter 3 and Chapter 5.
5. Conduct more empirical research that uses a multidisciplinary, mixed-methods approach, which is the scientific approach adopted in this dissertation (see Introduction, Section 1.6).

The review concluded by proposing the adoption of an integrative approach combining identity and networks to advance our understanding of collective action via CMC. Such an integrative approach was taken in subsequent chapters (3 and 5), which focused on identity and networks as micro-mobilization dynamics at work in online social movement campaigns.

All the chapters of this dissertation studied the case of the Movember Foundation and its US campaign on Twitter to promote men's health and collect donations for medical research. Chapter 3 focused on the communication networks generated by movement members during the campaign and the forming of a collective identity. In particular, Chapter 3 answered the following questions:

Question 3.1: How do online communication networks (a) structurally and (b) socially evolve over time in social movement campaigns?

Question 3.2: How do online communication networks shape and sustain the collective identity of the movements over time?

Question 3.3: What is the impact of online communication network structure and collective identity on individual and collective efforts in fundraising outcomes during social movement campaigns?

By using social movement theory and network theory and combining social network analysis with network visualizations, I found that the communication network of the Movember campaign has a three-layer structure that, on the whole, is maintained as the campaign unfolds. However, the robustness of such a structure fades over time: The communication network goes through late latency phases during which people decrease their active participation and move to the periphery of the communication network or even exit the campaign network. Inside this structure, movement members mostly adopt a conversational approach supported by communicative interactions between movement members and their audiences. In other words, the communication network remains socially intact over time. Furthermore, I found that the communication network structure shapes the collective identity of the movement, which appears as a connected but distributed entity. Its maintenance over time, however, is only thanks to a small number of highly committed members who are also very engaged in collecting donations for the campaign cause. Altogether, these findings showed that online communication network structure and collective identity might have an impact on individual and collective efforts in fundraising outcomes.

Chapter 4 focused on social identity and offered methodological tools (social identity classifiers) for social scientists to scale up online identity research to massive datasets derived from social media. This chapter answered the question:

Question 4: To what extent can the social identity of Twitter users be predicted based on their profile description?

Three social identity classifiers (relational identity, occupational identity, and collective action-oriented identity) were developed in two text classification experiments that automatically detected Twitter users' social identity on the basis of how they describe themselves in their profile description. In Chapter 4, we used an identity theory-based classification of online social identity to train the classifiers and showed that social theory can be used to guide natural language processing methods. In addition, this study showed that natural language processing methods can provide input to revisit traditional social theory, which is strongly consolidated in offline settings. This was evident in the results of the first experiment, where we obtained unsatisfactory classifier performances for some of the social identities types (political, ethnic/religious, and stigmatized identities). This evidence led us to reconsider and improve our theoretical classification, which was then successfully tested in the second experiment.

Chapter 5 focused on social identity and communication network positions as micro-dynamics at play in individual mobilization. This chapter offered an empirical test of the effect of movement members' online social identity and structural position in the communication network on individual mobilization outcomes. More specifically, it answered the question:

Question 5: How and why do movement members' online social identity and structural position in the communication network influence the individual amount of collected donations during online campaigns?

In this chapter, we focused on three types of social identity (relational, occupational, and collective action-oriented) as a motivator to engage in fundraising during campaigns and on network position (centrality and coreness) as a provider of opportunity structures to achieve successful outcomes. By adopting a multi-method approach combining automatic text analysis, social network analysis, and multivariate regression analysis, we found that only occupational identity (and not relational and action-oriented identities) has a significant effect on the amount of collected donations. In terms of network positions, the results showed that while occupying central positions in the Twitter communication network facilitated mobilization outcomes, people at the core of network communities collected less in donations than people at the periphery. Taken together, Chapters 3 and 5 show that identity and networks are important micro-mobilization dynamics to understand the effectiveness of online social movement campaigns.

Chapter 6 concluded the empirical section of the dissertation by examining the last two micro-mobilization dynamics, namely framing and emotions, emerging from interactive and communicative processes during mobilization. Chapter 6 answered two research questions:

Question 6.1: How does the dominant framing of social movement organizations characterize movement members' discourse in social media during campaigns?

Question 6.2: To what extent do a) movement members' adoption of the movement's dominant framing and b) the level of emotional involvement in members' framing processes affect movement members' fundraising outcomes during online campaigns?

By adopting a multi-method approach combining automated text analysis, the use of a plagiarism detector, network visualizations, and regression analysis, I found that almost one-third of the discourse that movement members generated on Twitter during the

campaign aligns with the Movember Foundation's dominant framing. However, the more movement members used the movement's language, slogans, and frames in their tweets, the less they collected in donations. By contrast, the use of emotional language in framing processes is positively associated with the amount collected in donations.

In summary, the collection of findings obtained in this dissertation shows that, by looking at the micro-mobilization dynamics of collective action, we can gain an important understanding of the mechanisms at work during online social movement campaigns and of the effectiveness of such campaigns in fostering communication processes related to the cause, obtaining important resources for the cause, developing a collective identity, and raising awareness. In the next section, I will discuss the theoretical, methodological, and practical contributions of these findings.

7.2 Contributions of the dissertation

This dissertation offers important contributions to theory and methodological approaches in a variety of fields, as well as practical contributions for individual activists and fundraisers, organizations and policy-makers. In the sections below, I will present and discuss the theoretical, methodological, and practical contributions of this dissertation.

7.2.1 Theoretical contributions

This dissertation provides four theoretical contributions. First, it deepens our understanding of micro-mobilization dynamics by taking a micro-level perspective to study the effectiveness of online social movement campaigns. This dissertation shows that people who adhere to social movements are important actors for the success and effectiveness of collective action in an environment characterized by the pervasive presence of social media and where individual agency has become important in the organization and outcomes of collective action (see Introduction, Section 1.2.2). This dissertation addresses the relationship between online and offline mobilization by tracking and linking movement members' online identities, communication exchanges, fundraising outcomes, organization of events, and socio-demographics. In this way, the dissertation contributes to current debates around the impact of social media on collective action, its organization, and individual participation (Bennett & Segerberg, 2015; Earl et al., 2014; Earl & Kimport, 2011; Gerbaudo & Treré, 2015; Hara & Huang, 2011; Murthy, 2018). I offer a concrete research agenda with conceptual and methodological research directions that are useful for studying the impact of social media in social movements (Chapter 2). In addition, the collection of empirical studies (Chapters 3–6) advances our understanding of online tactical repertoires and forms of activism by empirically testing their

effectiveness. The variety of dynamics and outcomes investigated in this dissertation required the combination of theories on identity from the traditional social movements field (e.g., Melucci, 1996; Polletta & Jasper, 2001; Snow, 2001) and social psychology (Stryker et al., 2000; Turner et al., 1987; e.g., van Stekelenburg & Klandermans, 2013; van Zomeren et al., 2008), theories of networks (e.g., Borgatti & Everett, 2000; Diani & McAdam, 2003; Everett & Borgatti, 2005; Freeman, 1979; Wasserman & Faust, 1994), framing (e.g., Benford & Snow, 2000; Snow et al., 2014), and communication (e.g., Bennett & Segerberg, 2012, 2013; Mattoni & Treré, 2014). In line with Della Porta and Diani (2015), I show that social movement studies – as a scientific, or “organizational” (DiMaggio & Powell, 1983), field of investigation and theorizing – can benefit from research using an interdisciplinary theoretical perspective.

Second, this dissertation contributes to the study of new forms of organization that are produced by technological innovation (e.g., the advent of social media) in interaction with social movements (e.g., online campaigns). As social movements are sources of innovation and social change (King & Soule, 2007; Rao, Morrill, & Zald, 2000), this dissertation helps to understand both emergent networked organizational forms visible on the Internet and the role of SMOs in contemporary collective action. Some scholars argue that social media have become the “organizing agents” of collective action (Bennett & Segerberg, 2012, 2013), and that SMOs have lost their role as necessary actors in mobilization, which becomes a form of “organizing without organizations” (Shirky, 2008). By contrast, this dissertation provides evidence of the important role of SMOs as organizing agents in social movements. Although SMOs might have a more flexible and decentralized role in the organization and coordination of collective action than it had before the advent of social media (Bimber et al. 2012; Caren, Jowers, and Gaby 2012; Kreiss 2012; Walker and Martin 2018), the way in which SMOs are adapting to these changes makes them among the principal actors innovating the concept of organization and organizing. This dissertation shows that SMOs can use social media to both mobilize and organize for social change. Findings from this dissertation provide insights to organizations about new ways of reaching their goals that are given not merely by the media used but also by the people inside this media environment. People’s use of social media breaks down boundaries within organizations so that the latter can exploit personal networks when organizing campaigns (as shown, for instance, in Chapters 3 and 5). When SMOs embrace these changes in the way they organize and mobilize, they evolve, endure over time, and expand transnationally (Bimber et al., 2012; Caren et al., 2012; Walker & Martin, 2018). This dissertation provides an example by analyzing the case of the Movember Foundation. Based on an idea that two friends came up with in 2003, the foundation has become an SMO that has altered the traditional meaning of organizing and membership within SMOs

by incorporating social media into their organizing, spreading the movement worldwide, facilitating communication between members, and, ultimately, achieving social change.

Third, this dissertation contributes to media and communication research by showing the potential of social media as platforms to study communication processes operating in different contexts at macro- and micro-levels. The role of communication processes generated by people during online mobilization is predominant in the body of work presented (see, for instance, Chapters 3, 5, and 6). In this regard, the presented studies heed calls for research into how communication technologies transform public online communication (Barberá et al., 2015; Bennett & Segerberg, 2014, 2015; González-Bailón & Wang, 2016; Lewis et al., 2014). This dissertation shows the various ways through which “communication repertoires” (Mattoni, 2013; Mattoni & Treré, 2014) can be realized and how communication can be used as a form of organization. Chapter 2, for instance, provides a research agenda on the role of computer-mediated communication in identity processes that offers theoretical and methodological venues of interest for media studies. In addition, Chapter 6 shows how social media favor the authenticity of communication processes and allow people to communicate and frame messages in personalized ways.

Fourth, this dissertation answers calls for more research into the mechanisms driving voluntary and pro-social behavior (Bekkers & Wiepking, 2011; Fussell Sisco & McCorkindale, 2013; Jones et al., 2013; Lovejoy & Saxton, 2012; Maher et al., 2014; Smitko, 2012; Thackeray, Burton, Giraud-Carrier, Rollins, & Draper, 2013). Movements such as Movember have philanthropic goals as they aim for advocacy causes (Jacobson & Mascaro, 2016). Studying individual participation in campaigns where people are asked to voluntarily engage in fundraising activities can provide information about the motivations and opportunities that people have toward giving, charity, and advocacy, as shown in Chapter 5. In addition, this dissertation contributes to deepening our understanding of the role of social media in transforming the practices of non-profit organizations. In particular, Chapters 3, 5 and 6 show that social media can be used not only for information distribution and generating attention, but also for their mobilization capabilities in getting resources from voluntary fundraising. The findings in these chapters can also provide insights about the use of social media data in public health research, as scholars in the field have called for (Chou et al., 2013; Gruebner et al., 2017; He, Veldkamp, & de Vries, 2012; Thackeray, Burton, et al., 2013; Thackeray, Neiger, et al., 2013; Tsai & Papachristos, 2015; Wehner et al., 2014). As the Movember campaign is a health-related social movement, this dissertation investigates how Twitter can be used for health communication and awareness, as well as medical fundraising purposes. This dissertation speaks to researchers interested in how social movement framing changes the rules in health advocacy, as in the case of cancer movements, and influences medical knowledge and the distribution of

medical research funds (Best, 2012), public health awareness (Bail, 2016; Centola & van de Rijt, 2015), and engagement (Bail et al., 2017).

7.2.2 Methodological contributions

This dissertation provides two methodological contributions. First, it shows the potential of adopting a multidisciplinary, mixed-method approach in social science research. The studies in this dissertation use systematic literature reviewing (Chapter 2), social network analysis and network visualizations (Chapter 3, Chapter 5, and Chapter 6), manual and automatic content analysis (Chapter 4 and Chapter 6), statistical regression analysis (Chapter 5 and Chapter 6), machine learning and natural language processing (Chapter 4). By combining these methods and techniques, I show that the adoption of a multidisciplinary, methodological approach not only boosts rigorous empirical research using such social media data and data triangulation (Chapters 3–6), but can also provide social scientists with input to revisit traditional social theory, which is often strongly consolidated in offline settings (Chapter 4). In addition, Chapter 2 provided a systematic review of methodological approaches and opened new research avenues in several fields in the social and computational sciences.

Second, this dissertation offers innovative applications and tools for social science research using large datasets. Social media have increased the possibilities of conducting research that is important to society (e.g., Bail et al., 2017; Gruebner et al., 2017; Lazer et al., 2009; Nguyen, 2017; Steinert-Threlkeld, 2018), and this dissertation shows the potential for mixed-methods and computational approaches to deal with the complexity of large datasets from social media. For example, the work presented in Chapter 4 provides social scientists with three social identity classifiers grounded in social theory that can scale up online identity research to large datasets, as illustrated in Chapter 5. Social identity classifiers can assist researchers interested in the relation between identity and language, human behaviors, and action in a multitude of social science disciplines.³⁷ Furthermore, the collection of studies presented in this dissertation offers new ideas on using and combining existing methods, techniques, and software to analyze large text data (Chapter 6) and network data (Chapter 3 and 5). In this vein, Appendix F at the end of this dissertation provides information to access the scripts and codes used in the chapters.

³⁷ Reebroek (2018) is a recent example of a study using the social identity classifiers developed in Chapter 4 to investigate engagement behavior in online brand communities.

7.2.3 Contributions to practice

In this dissertation, I consider online social movement campaigns as a new form of societal dialogue between individuals, organizations, and policymakers to achieve social change and find solutions to societal problems. As highlighted in the Introduction (Section 1.8), this dissertation's findings offer practical contributions for individual activists and fundraisers, multiple organizations (e.g., social movements, health advocacy, non-profit), and society at large.

Practical contribution for individual activists, movement members and fundraisers. This dissertation shows the value of individual activists, movement members, and fundraisers as actors involved in the organization and in the outcomes of collective action via online means. Results from the presented studies inform people interested in joining movements, participating in campaigns, or engaging in fundraising causes that social media can be used for “good” to contribute to social change by joining causes they believe in. In this way, citizens can directly engage and collaborate in the solution of societal problems in the view of “participatory democracies” (Ruijter, Grimmelikhuijsen, & Meijer, 2017).

Chapter 2 reviews several studies analyzing how computer-mediated communication (CMC) offers organizational means to garner information, coordinate, and promote mobilization. More specifically, Chapters 3, 5, and 6 offer examples of how Twitter's affordances offer easy, fast, and costless ways to foster communication processes that are fundamental in mobilization to connect individuals participating in the campaign. Nonetheless, findings from the presented studies also show the importance of embedding online tactics in a broader tactical mix that involves offline means. Results from Chapter 3, for instance, show that movement members might use Twitter to set up the campaign and spread the voice, but they are rarely involved in the long term as they might move to other social media, adopt other online tactics, or move their action offline straightaway. By tracking and linking online and offline action repertoires, Chapters 5 and 6 show that mobilization outcomes can be achieved by considering what people do offline, such as via the organization of events. Although social media might make mobilization easier, offline means are still important to assess the effectiveness of online social movement campaigns.

Practical contributions for organizations. The body of work presented in this dissertation provides valuable insights into the effective organization of online campaigns for multiple types of organizations. SMOs, for instance, learn about the mechanisms driving individuals' participation in online campaigns and use this knowledge to preserve their role in the organization of collective action in an era characterized by individual

agency and high “networked individualism” (Wellman et al., 2003). For example, Chapter 3 shows that organizing a long campaign is challenging because it is hard to keep people engaged in the cause. Therefore, SMOs might organize shorter campaigns and invest more in the launch phase in order to create awareness ahead of time. Chapter 5 shows the identity profiles of successful movement members that SMOs can target and involve as pivotal actors in their mobilization efforts. For example, people with salient occupational identities might be more willing to invest their time and resources in the workplace to promote the campaign and involve others in taking action. Movement members who have high communication potential to reach out to many others in the network because they are central in the communication process might be able to exploit this advantage to collect more donations for the campaign’s cause. Chapter 6 shows the importance of framing processes as factors explaining support for and participation in SMOs, but it also underlines that authenticity of communication and the use of emotional language are particularly important to achieve mobilization outcomes.

Furthermore, SMOs gain an important understanding of the disadvantages of social media use in mobilization. As explained in the Introduction (Sections 1.1 and 1.2.2), social media foster large participation rates because it is relatively easy to engage in online activism. However, as some critics argue, such online activism might produce weak and lazy forms of collective action that do not translate into concrete, meaningful (offline) action (Gladwell, 2010; Kristofferson et al., 2014; Lewis et al., 2014; Morozov, 2009). Chapter 3, for instance, shows that social media can easily produce a large volume of discussion involving massive crowds, but that only a few movement members remain engaged online until the very end of the campaign. Nonetheless, those who do are particularly engaged in fundraising for the cause. In a similar vein, Chapter 6 shows that Twitter is quite effective at spreading the movement’s dominant frame, but there is also a risk that people will simply rebroadcast (retweet) the message as an automatic, mechanical act, which can be considered a lazy form of participation: Although retweeting amplifies the volume of the discussion, it might not really make any concrete, meaningful contributions, as the results of the chapter show.

Understanding the advantages and disadvantage of social media use in online campaigns can help SMOs develop campaign strategies that increase the effectiveness of such forms of collective action. There is no doubt that incorporating social media in such strategies is beneficial. Nevertheless, the adoption of a tactical mix combining online and offline means can improve the chances of successfully achieving the goals. These insights are important not only for SMOs but also for advocacy and non-profit organizations in health care and other fields, as they can provide valuable insights about effectively organizing online campaigns. For example, health-focused organizations can gain an

important understanding of the mechanisms underlying Twitter fundraising campaigns for medical research and health programs.

Contributions for policy-makers and government organizations. Online cancer awareness campaigns, like the one analyzed in this dissertation, represent concrete actions that can contribute to finding solutions to one of the most pressing problems in our society. As explained in the Introduction (Section 1.6), this dissertation starts with a social problem (cancer) that calls for social change and analyzes the actions (social movement campaigns) that people and organizations take to solve the problem and how technologies (social media) can be used as a possible way to find a solution to the problem. Policy-makers need to heed and be responsive to such campaigns. The results laid out in this dissertation can support policymakers seeking to draft policies that improve public health by using social media to create health awareness and promoting voluntary online fundraising. Furthermore, the dissertation's findings can inform government organizations on the impact that technologies, such as social media, have on collective action for social problems. In this way, government organizations can embrace social media to enhance their performance and legitimacy and engage citizens in processes of coproduction of policies (Grimmelikhuijsen & Meijer, 2015; Meijer, 2014; Meijer & Thaens, 2013) that can solve important societal problems of our time.

7.3 Limitations of the dissertation

This dissertation presents two main limitations. Recognizing such limitations is the first step to avoid insights that are too simplistic because they are based on untested assumptions or anecdotes and isolated cases (Earl et al., 2014). First, this dissertation is bounded by the research design and methods in the various chapters. Although all such choices were aimed at identifying mechanisms that relate to the generic principles of many other examples of online social movement campaigns, the generalizability of the studies in this dissertation might suffer from *selection bias* due to the use of a particular case study (Movember) on a specific social media platform (Twitter). In addition, this dissertation's study of micro-mobilization dynamics is limited to four that have traditionally been addressed in social movement literature: identity, social networks, framing, and emotions. The presented studies did not address each dynamic in a comprehensive way nor consider interactions with other micro- (e.g., political interest, income, socio-demographics), meso- (e.g., organizational networks, forms, leadership, and tactical repertoires), and macro-level (e.g., broader structural and cultural conditions, historical contexts, political opportunities) dynamics that play a role in the effectiveness of online social movement campaigns. Furthermore, with the exception of Chapter 3, the studies presented in this dissertation

did not primarily take the time dimension into account. As social movements are dynamic processes (e.g., Della Porta & Diani, 2006), networks structures and individuals' positions in such structures, as well as identity processes, framing, narratives, and emotional involvement, do vary over time – not only as online campaigns unfold but also as social movements evolve over the years. In Section 7.4 below, I present possible avenues for future research that might address these limitations.

Second, this dissertation is predominantly based on social media data. The use of this type of data carries several biases and limitations that scholars in multiple disciplines have previously addressed (for reviews and reflections, see, among others, boyd & Crawford, 2012; Chang, Kauffman, & Kwon, 2014; González-Bailón et al., 2014; Lazer et al., 2009; McFarland & McFarland, 2015; Steinert-Threlkeld, 2018; Tufekci, 2014). The empirical chapters of this dissertation use complete (public) Twitter data from officially registered movement members combined with data provided by the Movember Foundation to study communication processes, contents, personal characteristics, behaviors, activities, and outcomes during large-scale health campaigns. However, owing to the Twitter focus, the findings' generalizability is limited to the Twitter population (*social media population bias*). The Twitter population is different from and only partially representative of the general population, as some social groups may be overrepresented (McFarland & McFarland, 2015; Nguyen, 2017; Steinert-Threlkeld, 2018). In addition, users who do not make their tweets public are not included in the population. Methodologically, the use of large social media populations makes statistical tests very sensitive and produces a surplus of statistically significant results (McFarland & McFarland, 2015). In this dissertation, I sought to address some of the consequences related to the *social media population bias* by a) linking information of Twitter users with data provided by the Movember Foundation (e.g., gender, experience in the campaign) in order to correct for biases regarding the population's composition (e.g., Wang, Rothschild, Goel, & Gelman, 2015) and b) increasing the accepted statistical significance level to 0.001 so as to reduce the bias resulting from large samples (McFarland & McFarland, 2015). Two additional options are available to improve the quality of the analysis in future research: carry out a data segmentation of the population in terms of their location and activity levels (McFarland & McFarland, 2015; Wang et al., 2015) and address relative changes over time (e.g., Zagheni & Weber, 2015). In addition, the use of a single data source (Twitter) causes a *social media platform selection bias* because no comparison across other social media platforms was made. Future research can test whether the mobilization dynamics and related outcomes obtained in this dissertation are confirmed on other social media platforms (e.g., Facebook) in order to expand the insights to the broader online context. Nonetheless, comparing different data sources with each other is very challenging because it is hard to obtain data from some social media platforms that have quite rigid policies (for a review, see Steinert-Threlkeld,

2018) and to track down and link all the social media accounts someone has. In addition, as addressed by Nguyen (2017), it can be difficult to identify the real causal factors behind observed differences (e.g., is a difference in the effects of network positions on individual mobilization outcomes caused by different user populations or by the specific medium's characteristics?). Although there is potential for Twitter as a data source (as explained in Section 1.5 of the Introduction and throughout this dissertation), it is important to develop an awareness of the challenges that research based on Twitter data poses. When doing research involving social media and, more broadly, communication technologies, there is always the risk that such technologies will quickly become obsolete. As Bimber et al. (2012, p. 11) write, "in a time of rapid technological change, any one tool is likely to be supplanted or modified by new ones in the space of a few years." Academic research using Twitter data is dominant in several fields, and it seems Twitter will continue to be the preferred data platform for social scientists (Steinert-Threlkeld, 2018). Thanks to the easy data access and the large user-based network size, Twitter has been defined as the "model organism" for social media studies (Tufekci, 2014). Nonetheless, this does not mean that Twitter is the best data provider or the best social media platform, nor that it has no limitations (it has many, as discussed above).

7.4 Directions for future research

In this section, I propose and discuss the most promising directions for future research.

7.4.1 Expand the study of the micro-dynamics of collective action

In this dissertation I focused on four key micro-mobilization dimensions (identity, social networks, framing, and emotions) and related processes that have traditionally been addressed in social movement literature. In this light, I call for future research that validates the findings of this dissertation by using other types of online social movement online campaigns – not only in health, such as Pink Ribbon for breast cancer or SunSmart for skin cancer,³⁸ but also other social issues, such as the environment, to deepen our understanding of micro-mobilization dynamics and on how SMOs generate awareness about their causes. In addition, the collection of presented studies is far from exhaustive and does not cover all the aspects related to these four dynamics, for which future research can be pushed forward in multiple ways. In the following, I will briefly elaborate on a few ideas.

Identity. The systematic review presented in Chapter 2 already offers plenty of ideas on how to push forward with research into individual, social, and collective identity in the

³⁸ For more information, see the Pink Ribbon International (<http://pinkribbon.org/about/>) and SunSmart programs (<http://www.sunsmart.com.au/about>).

study of social movements and collective action. In this dissertation, I focused on social (Chapter 4 and Chapter 5) and collective identity (Chapter 3). The ways of addressing and measuring these identity types can be improved and tested in various ways. More validation of the social identity classifiers is encouraged, in particular in relation to people's offline identity. Collective identity, instead, can be conceptualized in different ways than the systemic unity of the network, as I did in Chapter 3. Future research could look at more symbolical collective identification processes by looking at the actual content of those identities in social media text data. More qualitative research can be beneficial in these terms. However, because the findings from the presented studies did not always support a strong identity effect on mobilization outcomes, future research should be cautious about empirical findings that cannot really produce additional value.

Networks. Assessing the role of pivotal actors in online mobilization is important to understand the organization and outcomes of collective action (González-Bailón et al., 2013; González-Bailón & Wang, 2016; Poell et al., 2015). As shown in Chapters 3 and 5, movement members are embedded in network structures generated from communicative interactions. Inside such network structures, people occupy specific positions that can provide them with opportunity structures able to constrain or facilitate mobilization outcomes. Future research could investigate how such network positions can be translated to different roles within the organizational structures of online campaigns. For example, in a series of projects carried out in parallel with this dissertation, Priante and Bucchi (2018) use network-making power theory (Castells, 2011; Padovani & Pavan, 2016) to translate actors' structural network positions in a Twitter communication network into power roles shaping the public discourse in science-related debates. By contrast, Beck (2018) uses theories of network and opinion leadership to assess pivotal online opinion leaders in health campaigns.³⁹ Future research in this direction can also shed light on online leadership and mobilization outcomes (Andrews et al., 2010; Morris & Staggenborg, 2004) by identifying leaders who can inspire, motivate other movement members, frame causes, and mobilize resources (Earl & Schussman, 2002). Leaders can be identified not only for the position they occupy in the network but also with respect to the role they play in online groups and teams, as shown in Chapter 6, or in leader–member relationships (e.g., DeRue, Nahrgang, & Ashford, 2015; Hogg, 2001; Hogg et al., 2005). In this vein, more in-depth, qualitative methods, such as netnographic approaches or interviews, can illuminate the micro-processes at work. Studies in this direction can also provide insights for research on online community leadership and online opinion leadership.

³⁹ Beck (2018) was conducted under my supervision as part of the University of Twente's bachelor's program in International Business Administration.

Framing and emotions. As Chapter 6 showed, the study of framing and emotional languages is important to understand people's participation in collective action. Future research could expand the study of framing in social movements by identifying different stages of frame development not only in terms of individual variations and roles but also over time (see Section 7.4.3 below). In addition, looking more in depth at what people say in the campaigns is of great relevance. In a project carried out in parallel with this dissertation, Awlad Wadair (2016) looked at what people were writing in their tweets during the Movember campaign to identify whether there was any share of knowledge about technologies used to prevent, diagnose, and treat cancer.⁴⁰ In line with previous research (e.g., Bravo & Hoffman-Goetz, 2015; Jacobson & Mascaro, 2016; Prasetyo et al., 2015), the results from this study reveal that only 1.4% of tweets were about health technologies for cancer detection, which shows that campaigns on Twitter might be good when it comes to talking about health topics but not really for knowledge sharing (Awlad Wadair, 2016). In another project studying the SunSmart campaign to prevent skin cancer⁴¹ in Australia and New Zealand, Schindler (2018) combined sentiment and content analysis to detect people's opinions on the adoption of health-preventive behaviors and found that only a small number of tweets were health-opinion related, whereas the majority of the tweets were informative about taking precautions to prevent skin cancer. Future research should push ahead with an analysis of the contents produced during online social movement campaigns in order to deepen our understanding of their effectiveness at spreading messages related to their causes. Several methodological options are available to perform this type of analysis, one of which is topic modeling (Hong & Davison, 2010; Karami, Dahl, Turner-McGrievy, Kharrazi, & Shaw, 2018; Yang, Kolcz, Schlaikjer, & Gupta, 2014).

7.4.2 Expanding the study of the interaction between micro- and macro-dynamics in online social movement campaigns

This dissertation focuses on individuals and the micro-level dynamics in online social movement campaigns. However, the study of social movements can benefit from more research into the interaction between the micro and macro levels (Eder, 2015). To understand social movement outcomes, it is important to combine both factors related to agency, such as movement members' action, and contextual factors, such as political, cultural, and community-level opportunities (Edwards & McCarthy, 2004). In fact, not only are movement members conditioned by structural factors but they can change such

⁴⁰ Awlad Wadair (2016) was conducted under my supervision as part of the University of Twente's bachelor's program in Advanced Technology.

⁴¹ Schindler (2018) was conducted under my supervision as part of the University of Twente's bachelor's program in International Business Administration.

structures, recognize opportunities in the structures, and exploit them to achieve social change (Tarrow, 1998). In addition, little is known about how movement members use social media to identify and exploit such opportunity structures (Garrett, 2006). Thus, future research can expand the study of micro-mobilization dynamics to include the interactions between micro- and macro-dynamics in online social movement campaigns. An additional venue to explore is team dynamics in online campaigns and how they relate to individual-level factors. Chapters 5 and 6 partially addressed team participation and team leadership as control variables, and the results showed significant effects on individual mobilization outcomes. These dynamics merit further investigation. Research on team effectiveness in social movement campaigns is scant (Andrews et al., 2010; van den Broek et al., 2017), however, because social movement research has become very movement-centric in recent years (e.g., Walder, 2009), which shows a lack of theorization on teams as a key aspect of movement dynamics. Thus, future work can address research questions not only on individual-in-teams but also on teams-in-movements effectiveness. In a few parallel projects, we investigated the role of diversity in teams and community-level factors on fundraising performance during online social movement campaigns by conducting a multi-level statistical analysis (van den Broek et al., 2017). We also studied how team leaders organize and coordinate their teams to achieve outstanding fundraising performances using interviews (van 't Erve, 2018).⁴²

7.4.3 Tracking mobilization dynamics over time

As social movements are dynamic processes (e.g., Della Porta & Diani, 2006), large-scale studies over time can provide important insights into the formation, development, institutionalization, and failure of social movements (e.g., Barberá et al., 2015; González-Bailón & Wang, 2016; Mattoni & Treré, 2014; Pavan, 2017; Tindall, 2004). The amount of available social media data offers opportunities for this type of research. In spite of the challenges of longitudinal analysis due to the actual access to available social media data, which is often limited because of data provider restrictions (see Section 7.3 above), I propose that future research exploit the possibilities offered by computational social sciences and multidisciplinary expertise even further and use computational methods other than the ones adopted in this dissertation, such as neural networks and deep learning. In addition, studies using an experimental design (e.g., Vaillant Gonzalez et al., 2015; van de Rijt et al., 2014) can help assess the conditions influencing mobilization dynamics over time in controlled settings. Research of this type can benefit both social movement studies

⁴² van 't Erve (2018) was conducted under my supervision as part of the University of Twente's master's program in Business Administration.

and communication and media research interested in the evolution of social media affordances (Bennett & Segerberg, 2015; Earl et al., 2015).

7.4.4 From online to offline collective action

The advent of social media has offered researchers in various disciplines almost endless opportunities to study new forms of online activism (for reviews, see Earl et al. 2014; Earl and Kimport 2011; Hara and Huang 2011) and the offline facilitation of online activism (Earl et al., 2014; Earl & Kimport, 2011). Yet, there have been calls in the literature for more research into the translation from online to offline action (Bail, 2016; Bail et al., 2017; Byrne, 2007; Choi & Park, 2014; Coppock et al., 2016; Earl et al., 2014; González-Bailón & Wang, 2016; Lewis et al., 2014; Mattoni & Treré, 2014; Mercea, 2012; Schumann & Klein, 2015). Studies in this dissertation have addressed these calls (see, for instance, Chapter 5 and Chapter 6) by tracking and linking movement members' online and offline tactics, such as online Twitter activities, collected donations, and the organization of offline events. I propose that future studies push this type of research forward in order to provide an even better understanding of how online social movement campaigns are effective in their offline outcomes as well. For example, research involving direct contact with movement members (and not only the use of secondary, online data) can use online tracking to track online and offline behaviors of the members who are participating in the campaign. In addition, experimental designs (e.g., Centola & van de Rijt, 2015; Restivo & van de Rijt, 2014) can help assess the variation of online and offline mobilization dynamics and outcomes in controlled settings.

7.5 Concluding remarks

We live in an age where social media and digital technologies have a pervasive presence in our lives. The spread of Internet-based communication technologies, including social media, has challenged the practices of collective action and the role of individuals and organizations within social movements. Social media provide free and open platforms to organize, coordinate, and communicate about collective action in fast and cheap ways. The collection of findings obtained in this dissertation showed that, by looking at the micro-dynamics of collective action, we can gain important insight into the mechanisms at work during online social movement campaigns, as well as the effectiveness of such campaigns at achieving social change by fostering communication processes related to the cause, obtaining important resources for the cause, developing a collective identity, and raising awareness. The rise of social media has also offered rich, large-scale, longitudinal data sources to study social phenomena. Conducting research with a societal impact is

important and can be achieved by connecting the creation of knowledge with possible practical applications or solutions to social problems.

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Appendices

APPENDIX A: Data Extraction Matrix (Chapter 2)

APPENDIX B: Twitter data and creation of the dataset (Chapters 3, 5 and 6)

APPENDIX C: Temporal bracketing strategy (Chapter 3)

APPENDIX D: Robustness checks (Chapter 5)

APPENDIX E: Manual annotation of the tweets to include in the components (Chapter 6)

APPENDIX F: Guideline for the GitHub repository

APPENDIX A | Data Extraction Matrix (Chapter 2)

The data-extraction form (Table A1) contains information about author(s), year, perspective, key concepts, methods and themes extracted from the articles analyzed in Chapter 2.

Table A1. Data Extraction Matrix used as a repository for general (title, authors, journal) and specific (concepts, theories, methods, key findings) information related to the review’s research questions.

Author(s)	Year	Perspective	Identity level			Identity Phase	Type of collective action		Method	Themes	
			Col	Soc	Ind		CMC-based	CMC-supported		Identity is explanatory	Identity is the outcome variable
Adegoju and Oyeboode	2015	Other		X		Formation, Identification	X		Qual		X
Alberici and Milesi	2013	Social psychology		X		Identification	X	X	Quant	X	
Alberici and Milesi	2016	Social psychology	X	X		Identification	X	X	Quant	X	
Anderson, and Grace	2015	Other		X		Expression, building	X		Mixed		X
Beraldo and Galan-Paez	2013	Bridging	X			-	X		Mixed		X
Chan	2014	Social psychology		X		Identification	X	X	Quant	X	
Chan	2016	Bridging		X		Identification		X	Quant	X	
Chiluwa	2012	Other	X			Building	X	X	Qual		X
Choi and Park	2014	Bridging	X			Framing, Formation	X	X	Mixed		X
Chapman and Coffé	2016	Other	X		X	Construction	X		Quant		X
Coppock and Ternovski	2015	Social psychology		X		-	X		Mixed	X	
Coretti and Pica	2015	Bridging	X			Building	X	X	Mixed		X
Drissel	2013	NSM	X			Building, Adoption, Negotiation, Diffusion		X	Qual		X
Flesher Fominaya	2015	NSM	X			Construction		X	Qual		X

Reyes Soriano	2014	Other	X			Formation	X	X	Qual		X
Ribke and Bourdon	2015	Bridging		X		Expression, Formation	X	X	Qual		X
Rodan and Mummery	2016	NSM	X		X	Construction	X	X	Qual		X
Romanos	2015	Bridging	X			Formation, Development		X	Qual		X
Sanderson et al.	2016	Bridging		X		Management		X	Qual		X
Schumann, and Klein	2015	Social psychology		X		Consolidation	X	X	Quant	X	
Seo et al.	2014	Bridging		X		Identification	X	X	Quant	X	
Smith et al.	2015	Social psychology		X		Formation		X	Qual		X
Soon and Kluver	2014	Bridging	X		X	Building, Development	X	X	Qual		X
Stephan	2013	Other	X			Expression, Building		X	Mixed		X
Svensson	2012	Bridging	X			Negotiation, Maintenance	X		Qual		X
Svensson et al.	2015	NSM	X		X	Negotiation		X	Mixed		X
Tanczer	2015	Other		X	X	Building Maintenance, Identification		X	Qual		X
Thomas et al.	2015	Social psychology		X		Identification	X		Quant	X	
Treerè	2015	NSM	X			Building, Maintenance, Reclaim	X	X	Qual		X
Vicari	2014	Bridging	X			Building		X	Quant		X

APPENDIX B | Twitter data and creation of the dataset (Chapters 3, 5 and 6)

The Twitter data used in this analysis is derived from Nguyen et al. (2015), who use original data from the Twitter Datagrants (see the Introduction of the dissertation, Section 1.5) to find and match users in the US and the UK with both a Twitter account and a Movember member account in 2013 and 2014. As for their work, the authors needed to collect all possible tweets sent by a user to find a match. They used the Twitter API to collect up to 3,200 additional tweets not contained in the Datagrants archive. Therefore, in using the dataset by Nguyen et al. (2015) for my analysis, I had to filter tweets according to Movember-related keywords, geographical location, and timestamp. More specifically, I selected tweets with the keywords belonging to the Twitter Datagrants query for the Movember campaign:

“movember,” “movemeber,” “mobro,” “mobros,” “mosista,” “mosistas,” “mosister,” “mosocialistas,” “movemberlads,” “movemberstar,” “happymovember,” “movemberiscoming,” “links4movember,” “mofficials,” “moovember,” “mosoul,” “mospace,” “movem,” “movemb,” “movembe,” “movember_tine,” “mopictures,” “moselfie,” “supportthecause,” “supportthestache,” “prostate,” “testicular,” “mensbealth,” “mensbealthawareness,” “prostatecancer,” “prostatecancerawareness,” “testicularcancer,” “facesofmovember,” “facialhair,” “moustace,” “moustache,” “moustaches,” “noshavenovember,” “noshavetoday,” “novembeard,” “growamo,” “growthemo,” “gronyourbeard,” “gronyourmo,” “forthecause,” “signupmovember,” “justformenmo,” “showusyourmo,” “sharethemo,” “sboyomo,” “shavedown,” “shaveoff,” and “manupstacheup”

In addition, I selected US Twitter accounts by using a list of matched US Twitter and Movember users generated on the basis of Nguyen et al. (2015). Last, I filtered out tweets with a timestamp between 15 October 2014 and 16 December 2014. This resulted in a dataset of 14,970 tweets sent by 3,295 users.

APPENDIX C | Temporal bracketing strategy (Chapter 3)

To identify the four campaign's phases, I adopted a temporal bracketing strategy by following the method of Langley (2009). The identification of the phases was guided by carefully analyzing the distribution of members' Twitter activity over time and comparing it with the activity produced by the official Movember US account in order to identify the presence of particular peaks and troughs as "punctuated events." As Figure C1 (next page) shows, the weeks before the official beginning of the campaign (T1) were used to set the campaign in motion. The official Movember account sent tweets (black disks) almost every day, while also emphasizing the fundraising part of the campaign (black disks with larger size). The four campaign weeks (T2 and T3) follow a similar pattern: Most of the activity is concentrated during the week, and troughs always correspond to weekends. The first two campaign weeks (T2) have the highest level of Twitter activity. The official Movember account, for example, sent regular tweets every day. They mostly contained branded messages to motivate people to participate in the campaign and share their activity. In T3, in particular, many tweets were about the organization of offline events related to the campaign. Finally, the post-campaign phase (T4) identifies the echo-effects of the mobilization outcomes. Although the campaign had finished, the Movember account was still very active in stimulating the collection of donations. However, the overall volume of Twitter activity experienced a significant drop.

Figure C1. Distribution of Twitter activity of movement members during the Movember campaign (62 days) and the most important peaks and troughs.

The x-axis follows the 62 campaign days, whereas the y-axis indicates the volume of tweets, mentions, replies, and retweets sent by the movement members during the campaign. Black disks in the chart illustrate the days when the official Movember account sent out tweets about the campaign. Black disks with a larger size show that the tweets in question were about donations or fundraising activities. By contrast, days with grey disks stand for days on which Twitter activity was generated only by campaign participants. Weekend days have an "S" above the date label.

APPENDIX D | Robustness checks (Chapter 5)

This appendix shows the results of the robustness checks conducted in Chapter 5 (Table D1, D2, D3 and D4).

Table D1 shows the effects of the independent variables on whether people made/received a donation (dichotomous outcome). Using this dichotomous variable does not change the results regarding the effects of our two sets of independent variables.

Table D2 shows the effects of the independent variables on the average amount of collected donations (total amount of money collected divided by the number of donations made/received). Using this variable does not change the results regarding the effects of our two sets of independent variables.

Table D3 shows the models used in the Chapter where the core-periphery position variable has been replaced by its polynomial term to assess the curvilinear effect of core-periphery position on collected donations. The curvilinear effect is not significant.

Table D4 shows the models used in the Chapter with the addition of a dichotomous variable measuring the effect of having multiple salient overlapping (Model 2 and Model 4). The effect of this variable is not significant.

Sources of the data: Twitter data obtained via a Twitter datagrant on large online cancer awareness campaigns. Movember data provided by the US Movember Foundation.

Table D1. Multivariate analyses using logistic regression to explore the relation between online social identities, network positions, and whether people made/received a donation (dichotomous) during the 2014 US November campaign on Twitter (N=3,295).

Variables	Model 1 (Null)			Model 2 (Identity)			Model 3 (Network)			Model 4 (Full)		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
Relational Identity				-0.16	0.11	0.164				-0.16	0.11	0.162
Occupational Identity				0.32	0.11	0.003**				0.33	0.11	0.002**
Action-oriented Identity				-0.14	0.12	0.234				-0.13	0.12	0.277
Harmonic Centrality (ln)							1.99	0.65	0.002**	2.01	0.61	0.002**
Coreness							-0.25	0.06	0.000***	0.93	0.17	0.000***
Male	0.99	0.17	0.000***	0.99	0.17	0.000***	0.93	0.17	0.000***	0.93	0.17	0.000***
Experience	0.18	0.04	0.000***	0.18	0.04	0.000***	0.18	0.04	0.000***	0.18	0.04	0.000***
Tweets (ln)	0.59	0.08	0.000***	0.60	0.08	0.000***	0.70	0.09	0.000***	0.70	0.09	0.000***
Followers (ln)	0.06	0.03	0.028*	0.04	0.03	0.136	0.05	0.03	0.065	0.03	0.03	0.284
MoSpace URL	0.95	0.25	0.000***	0.97	0.25	0.000***	1.00	0.25	0.000***	1.02	0.25	0.000***
Event	0.78	0.74	0.290	0.80	0.74	0.279	0.83	0.74	0.267	0.84	0.75	0.262
In Team	0.74	0.10	0.000***	0.74	0.10	0.000***	0.74	0.10	0.000***	0.74	0.10	0.000***
Team Captain	0.15	0.12	0.214	0.17	0.12	0.179	0.15	0.12	0.237	0.16	0.12	0.187
Constant		-2.46			-2.47			-2.37			-2.38	
Log Likelihood		-1514.79			-1510.10			-1501.76			-1496.91	
Pseudo R2		0.07			0.07			0.08			0.08	

* p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).

Table D2. Multivariate analyses using Tobit regression to explore the relation between online social identities, network positions, and the average amount of collected donations during the 2014 US Movement campaign on Twitter (N=3,295).

Variables	Model 1 (Null)			Model 2 (Identity)			Model 3 (Network)			Model 4 (Full)		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
Relational Identity				-0.12	0.08	0.131				-0.12	0.08	0.106
Occupational Identity				0.19	0.07	0.009**				0.20	0.07	0.006**
Action-oriented Identity				-0.07	0.08	0.358				-0.06	0.08	0.410
Harmonic Centrality (ln)							0.50	0.16	0.003**	0.52	0.16	0.002**
Coreness							-0.15	0.04	0.000***	-0.15	0.04	0.000***
Male	0.94	0.14	0.000***	0.93	0.14	0.000***	0.90	0.14	0.000***	0.90	0.14	0.000***
Experience	0.13	0.02	0.000***	0.13	0.02	0.000***	0.14	0.02	0.000***	0.14	0.02	0.000***
Tweets (ln)	0.32	0.04	0.000***	0.32	0.04	0.000***	0.39	0.05	0.000***	0.39	0.05	0.000***
Followers (ln)	0.05	0.02	0.007**	0.04	0.02	0.036*	0.04	0.02	0.019*	0.03	0.02	0.093
MoSpace URL	0.73	0.21	0.001**	0.73	0.21	0.000***	0.76	0.21	0.000***	0.77	0.21	0.000***
Event	0.34	0.29	0.239	0.34	0.28	0.233	0.38	0.28	0.182	0.39	0.28	0.177
In Team	0.51	0.08	0.000***	0.50	0.08	0.000***	0.51	0.08	0.000***	0.51	0.08	0.000***
Team Captain	0.22	0.07	0.005**	0.23	0.07	0.004**	0.21	0.07	0.006**	0.22	0.07	0.004**
Constant	-0.42			-0.42			-0.38			-0.37		
Log Likelihood	-6071.59			-6067.78			-6062.98			-6058.83		
Sigma	1.79			1.79			1.79			1.79		

652 left-censored observations at Donations (ln) <= 0; 2,643 uncensored observations. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).

Table D3. Multivariate analyses using Tobit regression to explore the relation between online social identities, network positions, and the average amount of collected donations during the 2014 US Movement campaign on Twitter (N=3,295).

Variables	Model 1 (Null)			Model 2 (Identity)			Model 3 (Network)			Model 4 (Full)		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
Relational Identity				-0.17	0.11	0.152				-0.18	0.11	0.112
Occupational Identity				0.22	0.11	0.045*				0.25	0.11	0.026*
Action-oriented Identity				-0.08	0.12	0.500				-0.06	0.12	0.594
Harmonic Centrality (ln)							1.12	0.25	0.000***	1.15	0.25	0.000***
Coreness							-0.35	0.11	0.004**	-0.32	0.11	0.004**
Coreness*Coreness							0.02	0.03	0.417	0.02	0.03	0.420
Male	1.51	0.33	0.000***	1.51	0.22	0.000***	1.43	0.22	0.000***	1.43	0.22	0.000***
Experience	0.27	0.03	0.000***	0.27	0.03	0.000***	0.28	0.03	0.000***	0.28	0.03	0.000***
Tweets (ln)	0.74	0.06	0.000***	0.74	0.06	0.000***	0.83	0.07	0.000***	0.83	0.07	0.000***
Followers (ln)	0.05	0.03	0.050	0.04	0.03	0.126	0.04	0.03	0.175	0.02	0.03	0.389
MoSpace URL	1.06	0.31	0.001**	1.07	0.31	0.001**	1.12	0.31	0.000***	1.13	0.31	0.000***
Event	0.47	0.43	0.271	0.47	0.43	0.269	0.52	0.43	0.224	0.52	0.43	0.222
In Team	0.81	0.12	0.000***	0.81	0.12	0.000***	0.81	0.12	0.000***	0.80	0.12	0.000***
Team Captain	0.49	0.11	0.000***	0.50	0.42	0.000***	0.48	0.11	0.000***	0.49	0.11	0.000***
Constant		-1.40			-1.40			-1.23			-1.23	
Log Likelihood		-7090.48			-7087.99			-7075.30			-7072.30	
Sigma		2.67			2.66			2.65			2.65	

652 left-censored observations at Donations (ln) <= 0; 2,643 uncensored observations. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).

Table D4. Multivariate analyses using Tobit regression to explore the relation between online social identities, network positions, and the average amount of collected donations during the 2014 US Movember campaign on Twitter (N=3,295).

Variables	Model 1 (Null)			Model 2 (Identity)			Model 3 (Network)			Model 4 (Full)		
	b	s.e.	p	b	s.e.	p	b	s.e.	p	b	s.e.	p
Relational Identity				-0.15	0.12	0.217				-0.18	0.12	0.156
Occupational Identity				0.28	0.20	0.167				0.29	0.20	0.143
Action-oriented Identity				-0.07	0.12	0.554				-0.05	0.12	0.642
Multiple Identities (1=yes)				-0.07	0.22	0.746				-0.06	0.22	0.784
Harmonic Centrality (ln)							1.17	0.24	0.000***	1.20	0.24	0.000***
Coreness							-0.24	0.06	0.000***	-0.24	0.06	0.000***
Male	1.51	0.33	0.000***	1.51	0.22	0.000***	1.44	0.22	0.000***	1.44	0.22	0.000***
Experience	0.27	0.03	0.000***	0.27	0.03	0.000***	0.28	0.03	0.000***	0.28	0.03	0.000***
Tweets (ln)	0.74	0.06	0.000***	0.74	0.06	0.000***	0.84	0.07	0.000***	0.84	0.07	0.000**
Followers (ln)	0.05	0.03	0.050	0.04	0.03	0.120	0.03	0.03	0.200	0.02	0.03	0.412
MoSpace URL	1.06	0.31	0.001**	1.07	0.31	0.001**	1.10	0.31	0.000***	1.11	0.31	0.000***
Event	0.47	0.43	0.271	0.47	0.43	0.268	0.54	0.42	0.202	0.54	0.42	0.200
In Team	0.81	0.12	0.000***	0.81	0.122	0.000***	0.80	0.12	0.000***	0.80	0.12	0.000***
Team Captain	0.49	0.11	0.000***	0.50	0.11	0.000***	0.49	0.11	0.000***	0.50	0.11	0.000***
Constant		-1.40			-1.40			-1.25			-1.24	
Log Likelihood		-7090.48			-7087.94			-7075.63			-7072.59	
Sigma		2.67			2.66			2.65			2.65	

652 left-censored observations at Donations (ln) <= 0; 2,643 uncensored observations. * p<0.05; ** p<0.01; *** p<0.001 (two-tailed tests).

APPENDIX E | Manual annotation of the tweets to include in the components (Chapter 6)

The use of the plagiarism detector software WCopyfind carries two limitations. First, the software does not take spelling errors into account. Second, the value of the “Fewest Matches to Report” parameter (9) implies that WCopyfind does not report matches resulting from parsing strings of fewer than nine words. Therefore, if matches are found and reported by the software for the string “1 in 2 men will be diagnosed with cancer,” strings like “1 in 2 men are diagnosed with cancer” are not reported by the software.

To overcome these two limitations, I conducted a manual search of strings of words of the matches reported by the software as well as of portions of such strings in the tweets that were not assigned to any components. To conduct the search, I used the list of matched strings that were detected in the biggest components and were related to the dominant framing proposed by the Movember Foundation in the components.⁴³ Table E1 shows the results of the manual annotation. The list of strings illustrated in the Table was also used to create the chapter’s first independent variable (*Movember Framed Tweets*), which measures the adoption of the Movember movement’s dominant framing by movement members in the Twitter discourse. The sum of all TT values in the Table indicates the total number of tweets (27%) sent during the campaign period that contained at least one of the identified strings related to the movement’s dominant framing.

⁴³ I used the matched strings detected by the plagiarism detector in the eight biggest components. Five of them (3, 15, 20, 17, 61) are the one presented in the main analysis illustrated in Section 6.5 of Chapter 6. The remaining three components (2, 22, 75) were not included in the presented analysis due to the cut-off value selection. Nonetheless, the detected strings of such components were still closely related in content to the five biggest components. Therefore, I expanded the search to a larger number of components so to assure a more comprehensive annotation of the tweets.

Table E1. Manual annotation of the tweets: matched strings in the component and distributions of tweets detected by the plagiarism software (TWC), manually annotated tweets (TMA) and total distribution (TT).

C	Matched strings in the component	TWC	TMA	TT
3	the face of men's health by making a donation (to my moustache) a donation to my moustache support m journey by making a change/changing the face of men's health (by supporting) help me change the face of men's health help change the face of men's health this by making a donation help me to change the face of men's health this by donating help us change the face of mens health this by making a donation to I'm a Mo Sista helping change the face of mens health donate to my/our (hairy) effort(s) help (me/us) beat prostate/testicular cancer will be diagnosed with cancer 1 in 2 men will be diagnosed with cancer in their lifetime 1 in 7 men will be diagnosed with prostate cancer (in their lifetime) 1 in 4 adults will experience a mental health problem this year In 2014 more than 233000 men will be diagnosed with prostate cancer About 8820 cases of testicular cancer will be diagnosed in 2014 Testicular cancer is the most common cancer in (young) men help (me/us) raise/raising awareness We are in this together I'm growing a my mustache join my team and help My moustache is in need of your support Please donate Sign up for Movember to change the face of	2,076	308	2,384
15	donate to my/our (hairy) effort(s) donate to my efforts and help beat prostate cancer here help/Please make a donation; by making a donation help (me/us) beat prostate/testicular cancer	455	7	462
20	Movember's here and I'm looking for new Mo Bros and Mo Sistas for my team	305		305
17	Together we are changing the face of men's health change/changing the face of men's health Thank you XX for donating (to my efforts) Thank you XX for donating to Together we are changing the face of men's health we are in this together	198	44	242
61	1 in 4 adults will experience a mental health problem this year 1 in 4 adults will experience a mental health problem this year Take action and join my team 1 in 4 adults will experience a mental health problem this year Im taking action with join me	194		194
2	cases of prostate cancer will be diagnosed in 2014 About 8820 cases of testicular cancer will be diagnosed in 2014 Donate	181		181
22	I'm changing the face of men's health with Movember (join me)	160		160
75	changing the face of men's health join me by signing up	102		102
TOT				4,030

C = ComponentID; TWC = number of tweets detected by WCopyfind; TMA = number of manually annotated tweets added to the component after the manual search; TT = total number of tweets in the component

APPENDIX F | Guideline for the GitHub repository

This appendix provides a guideline to a GitHub repository (<https://github.com/annapriante/phd-dissertation-codes>) containing the scripts used in this dissertation. The online repository is organized as follows:

1. **communication_network.ipynb:** This is the code used to create the communication network used in Chapter 3 and Chapter 5. This code creates the network from the exchange of tweets, mentions, replies and retweets. Data used: Twitter data. Programming language used: Python.
2. **preprocessing_tweets.ipynb:** This is the code used for the text preprocessing of the tweets (remove URLs, punctuation, RT, @, #) to facilitate the identification of unique statements (Chapter 6). Data used: Twitter data. Programming language used: Python.
3. **preprocessing_tweets_LIWCanalysis.ipynb:** This is the code used for the text preprocessing of the tweets for the text analysis using LIWC (Chapter 6). Data used: Twitter data. Programming language used: Python.
4. **extract_URLs_from_tweets.ipynb:** This is the code used to extract the tiny URLs from the text of the tweets (Chapter 6). Data used: Twitter data. Programming language used: Python.

The codebook and code used to develop the social identity classifiers (Chapter 4) are available in a dedicated GitHub repository:

<https://github.com/annapriante/identityclassifier>

Summary

Social movement organizations (SMOs) widely use social media to organize collective action for social change, such as cancer awareness campaigns. However, little is known about how effective online social movement campaigns are at generating social change by translating online action into meaningful (offline) action. This dissertation examines the micro-mobilization dynamics at play that can explain the effectiveness of online social movement campaigns. The central research question of this dissertation is:

How and why do micro-mobilization dynamics explain the effectiveness of online social movement campaigns in achieving social change?

This dissertation comprises six chapters seeking answers to this question and presents research based on a multidisciplinary, mixed-method approach combining theories and methods from sociology, social psychology, communication science, and computational social science.

In this dissertation, I investigate four key micro-mobilization dynamics that play a role in mobilizing movement members: identity, networks, framing, and emotions. **Chapter 2** provides a systematic literature review of identity and collective action via computer-mediated communication (CMC). By reviewing 59 empirical studies published from 2012 to 2016, we find that empirical research on identity, collective action, and CMC is broad and diverse because of contributions from multiple disciplines, theoretical perspectives, and methodological approaches. Given the shortcomings in the findings, we derive a series of recommendations for future research directions, which also guide the empirical research presented in this dissertation.

All the empirical chapters of this dissertation study the case of the Movember Foundation and its US campaign on Twitter to promote men's health and collect donations for medical research. Twitter data was provided by Twitter, which introduced the Twitter #DataGrants pilot program in 2014 with the aim of granting a small number of research institutions access to public and historical data. The unfettered access to the Twitter archive, combined with additional data provided by the Movember Foundation, provides a unique opportunity to study the effectiveness of online cancer awareness campaigns by tracking and linking online and offline individual-level data.

Chapter 3 uses social movement theory and network theory to study the communication networks generated by movement members during the Movember campaign and the forming of a collective identity. In this single-author chapter, I find that the online communication network goes through late latency phases during which people

decrease their active participation and move to the periphery of the network or even exit the campaign network. Furthermore, I find that the communication network structure shapes the collective identity of the movement, which appears as a connected but distributed entity. Its maintenance over time, however, is only thanks to a small number of highly committed members who are also very engaged in collecting donations for the campaign cause. Altogether, these findings show that network structure and collective identity might have an impact on individual and collective efforts in fundraising outcomes.

Chapter 4 is a methodological study illustrating the development of automatic tools to detect Twitter users' social identity. This chapter offers tools (social identity classifiers) for social scientists to scale up online identity research to massive datasets derived from social media. An identity theory-based classification of online social identity is used to train the classifiers. This study shows that social theory can be used to guide natural language processing methods, and that natural language processing methods can provide input to revisit traditional social theory, which is strongly consolidated in offline settings.

Chapter 5 investigates the effect of movement members' online social identity and structural position in the communication network on individual mobilization outcomes. By adopting a multi-method approach combining automatic text analysis, social network analysis, and multivariate regression analysis, we find that only some types of social identity have a significant effect in predicting the amount of collected donations. In terms of network positions, the results show that while occupying central positions in the Twitter communication network facilitate mobilization outcomes, people at the core of network communities collect less in donations than people at the periphery.

Chapter 6 concludes the empirical section of the dissertation by examining the last two micro-mobilization dynamics, namely framing and emotions, emerging from interactive and communicative processes during mobilization. In this single-author chapter, I use a multi-method approach combining automated text analysis, the use of a plagiarism detector, network visualizations, and regression analysis to study the extent to which movement members' adoption of the movement's dominant framing and the level of emotional involvement in members' framing processes explain fundraising outcomes during online campaigns. I find that almost one-third of the discourse that movement members generated on Twitter during the campaign aligns with the Movember Foundation's dominant framing. However, the more movement members use the movement's language, slogans, and frames in their tweets, the less they collect in donations. By contrast, the use of emotional language in framing processes is positively associated with the amount collected in donations.

In summary, the collection of findings obtained in this dissertation shows that, by looking at the micro-mobilization dynamics of collective action, we can gain an important understanding of the mechanisms at work during online social movement campaigns and

of the effectiveness of such campaigns in fostering communication processes related to the cause, obtaining important resources for the cause, developing a collective identity, and raising awareness. Owing to its multidisciplinary approach, this dissertation offers theoretical contributions at the intersection of several fields of studies on social movements, social networks, media and communication, nonprofit organizations, and public health. Methodologically, this dissertation offers innovative applications and tools for social science research using social media, new ideas on how to use and combine existing methods, techniques, and software to analyze large datasets, and direct access to scripts, codes, and tools developed to support data collection, preparation, and analysis. In practical terms, the body of work presented in this dissertation provides multiple organizations (e.g., social movements, health advocacy, nonprofit) with valuable insights into the effective organization of online campaigns via social media. In addition, results from this dissertation can support policymakers and practitioners in framing policies that improve public health via voluntary online fundraising; and individual activists in organizing collective action to produce effective social change in a society characterized by the pervasive influence of social media.

Samevatting

Tweet je #Mo en red een Bro:

Micro-mobilisatiedynamiek en de effectiviteit van online campagnes door sociale bewegingen

Sociale bewegingen (social movements) maken op grote schaal gebruik van sociale media bij het organiseren van collectieve acties die ten doel hebben sociale veranderingen teweeg te brengen. Een voorbeeld hiervan zijn campagnes voor het vergroten van de bewustwording rondom kanker. Er is echter weinig bekend over de effectiviteit van deze online campagnes voor het realiseren van sociale veranderingen door middel van de overgang van online actie naar zinvolle (offline) actie. Dit proefschrift onderzoekt de dynamieken die een rol spelen bij micro-mobilisatie om hiermee de effectiviteit van online campagnes door sociale bewegingen te kunnen verklaren. De kernvraag van dit proefschrift is:

Hoe en waarom verklaren micro-mobilisatiedynamieken de effectiviteit van online campagnes van sociale bewegingen voor het realiseren van sociale verandering?

Dit proefschrift bevat zes hoofdstukken waarin antwoorden op deze vraag worden gezocht en waarin de resultaten van een multidisciplinair onderzoek worden gepresenteerd, gebaseerd op een mixed-methods aanpak. Deze aanpak combineert theorieën en methoden uit de sociologie, sociale psychologie, communicatiewetenschap en computationele sociale wetenschappen.

In dit proefschrift onderzoek ik vier belangrijke micro-mobilisatiedynamieken die een rol spelen bij de mobilisatie van de leden van een sociale beweging: Identiteit, Netwerk, Framing en Emotie. **Hoofdstuk 2** biedt een systematisch literatuuronderzoek naar identiteit en collectieve actie door middel van computer-verspreide communicatie (CMC: computer-mediated communication). Uit 59 empirische studies, gepubliceerd tussen 2012 tot 2016, blijkt dat er uitgebreid empirisch onderzoek is gedaan naar identiteit, collectieve actie en CMC en dat deze onderzoeken bovendien divers zijn vanwege de bijdragen vanuit verschillende disciplines, theoretische perspectieven en methodologische benaderingen. Gezien de tekortkomingen die in de onderzochte studies naar voren zijn gekomen, geven wij een reeks aanbevelingen voor toekomstige onderzoeksrichtingen. Aanbevelingen die ook richting geven aan het empirisch onderzoek dat in dit proefschrift wordt gepresenteerd.

De onderzoekscasus in de empirische hoofdstukken van dit proefschrift betreft de Movember Foundation en haar Amerikaanse campagne op Twitter ter bevordering van de gezondheid van mannen en de werving van donaties voor medisch onderzoek. Onderzoeksgegevens werden verstrekt door Twitter, dat in 2014 het Twitter #DataGrants-programma heeft geïntroduceerd met als doel een klein aantal onderzoeksinstellingen toegang te verlenen tot publieke en historische gegevens. De vrije toegang tot het Twitter-archief, in combinatie met aanvullende gegevens van de Movember Foundation, biedt een unieke gelegenheid om de effectiviteit van online bewustwordingscampagnes rondom kanker te bestuderen. In het bijzonder door de mogelijkheid om online- en offlinegegevens op individueel niveau te traceren en te koppelen.

Hoofdstuk 3 gebruikt de Sociale bewegingstheorie en Netwerktheorie om de communicatienetwerken en de collectieve identiteit te bestuderen die gedurende de campagne in de Movember beweging zijn gevormd. In dit hoofdstuk, door mij geschreven als enige auteur, blijkt dat het online communicatienetwerk late vertraging fasen doorloopt waarin mensen hun actieve deelname verminderen en naar de netwerkperiferie bewegen of zelfs uit het netwerk stappen. Ook blijkt dat de structuur van het communicatienetwerk van invloed is op de (collectieve) identiteit van de beweging die naar voren komt als verbonden doch gedistribueerde entiteit. Het onderhouden van het netwerk in de loop van de tijd vindt slechts plaats dankzij een klein aantal zeer toegewijde leden die ook zijn betrokken bij het werven van donaties voor de campagne. Al met al laten de bevindingen zien dat de netwerkstructuur en de collectieve identiteit van invloed kunnen zijn op de individuele en collectieve inspanningen voor de werving van fondsen.

Hoofdstuk 4 beschrijft een methodologische studie waarin de ontwikkeling van automatische classificatiealgoritmen voor het vaststellen van de sociale identiteit van Twitter gebruikers wordt geïllustreerd. Dit hoofdstuk biedt sociale wetenschappers onderzoeksinstrumenten (classificatiealgoritmen) die ingezet kunnen worden om online identiteit op basis van omvangrijke sociale media datasets te onderzoeken. Deze studie toont aan dat sociale theorie richting kan geven aan methoden voor de verwerking van natuurlijke taal (NLP: natural language processing) en dat deze (NLP-)methoden bijdragen aan traditionele sociale theorie, welke hoofdzakelijk offline-georiënteerd is.

Hoofdstuk 5 presenteert onderzoek naar het effect van de online sociale-identiteit van de leden van de beweging en het effect van hun structurele positie in het communicatienetwerk op de individuele wervingsresultaten. Met de toepassing van een mixed-methods aanpak waar automatische tekstanalyse, sociale netwerkanalyse en multivariate regressieanalyse zijn gecombineerd, blijkt dat alleen professionele identiteit (statistisch) significant is bij het voorspellen van de hoogte van de geworven donaties. Voor wat betreft de netwerkpositie laten de resultaten zien dat, hoewel het bezetten van

een centrale positie in het Twitter communicatienetwerk de micro-mobilisatie vergemakkelijkt, leden in het centrum van het netwerk minder donaties werven dan leden aan de periferie.

Hoofdstuk 6 sluit het empirische gedeelte van het proefschrift af met een analyse van de laatste twee dynamieken van micro-mobilisatie, Framing en Emotie, welke voortkomen uit communicatie tijdens de mobilisatie. In dit hoofdstuk, geschreven als enige auteur, heb ik gekozen voor een mixed-methods aanpak, bestaande uit een combinatie van geautomatiseerde tekstanalyse, een plagiaatdetector, netwerkvisualisaties en regressieanalyse. Via deze aanpak onderzoek ik in hoeverre de aanvaarding van de dominante framing van de beweging door de leden en de emotionele betrokkenheid bij de framing-processen de resultaten van de fondsenwerving tijdens de online campagnes verklaren. Het blijkt dat bijna een derde van de conversaties van de leden op Twitter tijdens de campagne in overeenstemming is met de dominante framing van de Movember Foundation. Daarentegen blijkt ook dat hoe meer de leden in hun tweets gebruikmaken van de taal, slogans en frames van de beweging, des te minder donaties zij werven. Daar staat tegenover dat het gebruik van emotie in het taalgebruik bij framingprocessen een positief effect heeft op de omvang van de donaties.

Samengevat tonen de bevindingen in dit proefschrift aan dat wij bij het bestuderen van de micro-mobilisatiedynamieken van collectieve actie een goed inzicht kunnen krijgen in de mechanismen die een rol spelen bij online campagnes van sociale bewegingen. Tevens krijgen wij hiermee inzicht in de effectiviteit van dit soort campagnes voor het bevorderen van doelgerichte communicatieprocessen, het verwerven van de noodzakelijke middelen, het ontwikkelen van een collectieve identiteit en het stimuleren van bewustwording. Vanwege de multidisciplinaire aanpak biedt dit proefschrift, op het kruispunt van verscheidene disciplines, theoretische bijdragen op het gebied van sociale bewegingen, sociale netwerken, media en communicatie, non-profitorganisaties en volksgezondheid. Op het gebied van methodologie biedt dit proefschrift vernieuwende toepassingen en hulpmiddelen voor het gebruik van sociale media bij sociaalwetenschappelijk onderzoek. Ook biedt dit proefschrift nieuwe ideeën voor het toepassen en het combineren van bestaande methoden, technieken en software om grote datasets te analyseren. Tot slot geeft het proefschrift vrije toegang tot de scripts, codes en hulpmiddelen die zijn ontwikkeld ter ondersteuning van dataverzameling, datavoorbereiding en data-analyse. In praktische zin biedt dit proefschrift aan verschillende typen organisaties (zoals sociale bewegingen, gezondheidsorganisaties en non-profit organisaties) waardevolle inzichten voor het effectief organiseren van online campagnes via sociale media. Bovendien kunnen de resultaten van dit proefschrift beleidsmakers en andere professionals van nut zijn bij het opstellen van beleid om de volksgezondheid te verbeteren via online fondsenwerving. Daarnaast kunnen ook individuele activisten de inzichten van dit proefschrift toepassen

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Anna
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About the Author

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Anna Priante was born on the 3rd of April 1990 in Arzignano, Italy. In parallel with her compulsory and university education, she carried out studies in music as a pianist and composer. Anna obtained a Bachelor degree in Sociology (*cum Laude*, 2012) and a Master degree in Sociology and Social Research (*cum Laude*, 2015) at the University of Trento (Italy), and won the “University of Trento Academic Merit Prize” twice (in 2012 and 2016). During her master studies, Anna spent five months as an Erasmus Exchange Student at Department of Global Political Studies at the Malmö University (Sweden). In addition, she was Teaching Assistant in the course of *Sociology of Science* (BSc) and *Communication, Science and Technology* (MSc), working together with prof. Massimiano Bucchi. In this way, she began her (still ongoing) collaboration with two Italian research groups on science,

technology and society: STSTN (Trento) and Observa Science in Society (Vicenza).

In May 2015, Anna obtained a 3-year PhD position at the Department of Public Administration of the University of Twente, under the supervision of prof. dr. Ariana Need (Public Administration), Dr. Michel Ehrenhard (Entrepreneurship, Strategy and Innovation Management), Dr. Djoerd Hiemstra (Computer Science) and Dr. ir. Tijs van der Broek (Entrepreneurship, Strategy and Innovation Management). Her multidisciplinary PhD project was funded by the *Tech4People* program of the university to study the effectiveness of Twitter cancer awareness campaigns. In this way, Anna became part of the #TwitterDatagrants team that in 2014 received one of the first six awarded Twitter datagrants. Part of her PhD research was published in the journal of *New Media & Society* and in the proceedings of the *Association for Computational Linguistics*. She presented her work at international conferences, such as the annual meetings of the *Academy of Management* and the *American Sociological Association*, and the *Sunbelt International Conference on Network Analysis*.

At the beginning of her PhD, Anna was part of a group of PhD students who founded the *IGS PhD Initiative Group* to promote multidisciplinary collaborations among PhDs of the Faculty of Behavioral, Management and Social Science of the University of Twente. During her PhD, Anna also served as reviewer for several journals, such as *New Media and*

Society, Public Understanding of Science, Technological Forecast and Social Change, and the *Journal of the Association for Information Systems*. In January 2018, she was appointed visiting graduate student at the Department of Sociology at the University of California, Los Angeles, working together with Prof. Edward Walker.

In May 2018, Anna obtained a position as researcher and lecturer at the Department of Business Administration, research group for Entrepreneurship, Strategy and Innovation Management (NIKOS), of the University of Twente. While completing the writing of her PhD dissertation, Anna was involved in thesis supervision and teaching at the bachelor and master level. In Autumn of the same year, Anna obtained the *University of Twente Incentive Fund* for talented female staff members to carry out another research visit in the US and further develop her career. In January 2019, Anna was promoted Assistant Professor at the NIKOS department.

Social movement organizations widely use social media to organize collective action for social change, such as cancer awareness campaigns. However, little is known about how effective online social movement campaigns are at generating social change by translating online action into meaningful (offline) action. This dissertation examines the micro-mobilization dynamics at play that can explain the effectiveness of online social movement campaigns. This book comprises seven chapters presenting research based on a multidisciplinary, mixed-method approach combining theories and methods from sociology, social psychology, communication science, and computational social science.

The findings show that, by looking at the micro-mobilization dynamics of collective action, we can gain an important understanding of the mechanisms at work during online social movement campaigns and of the effectiveness of such campaigns in fostering communication processes related to the cause, obtaining important resources for the cause, developing a collective identity, and raising awareness.