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**Participation in Online Health Communities and Perceived Social Support:
Elaborating Participation Types, Identification, and Interpersonal Bonds**

Committee:

Keri Stephens, Supervisor

Jay Bernhardt

Joshua Barbour

Erin Donovan

Craig Scott

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Support: Elaborating Participation Types, Identification, and
Interpersonal Bonds**

**by
Yaguang Zhu**

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Abstract

Participation in Online Health Communities and Perceived Social Support: Elaborating Participation Types, Identification, and Interpersonal Bonds

Yaguang Zhu, Ph.D.

The University of Texas at Austin, 2018

Supervisor: Keri K. Stephens

Presently, an increasing number of people with chronic diseases exchange social support using online health communities (OHCs). They often gain knowledge from interacting with like-others and improve self-management of their disease. Analyzing people's online participatory behaviors boosts our understanding of the impact of OHCs. This dissertation project describes two interrelated studies that examine the relationship between participation types, group communication mechanisms, and social support. Together, they reveal how people participate in OHCs and provide understanding of the nuanced communicative mechanisms found in online communities that might help people cope and heal when they have a chronic disease.

Study One critiques previous methodological approaches as limited by a static conceptualization of participation that (1) dichotomized people's online interaction (e.g., low participation vs. high participation) and (2) did not allow for variability of OHC participation. To fill the gap, this study advances the conceptualization of OHC participation by defining participation in two equally important dimensions: level of participation (ranging from complete lurking to active posting) and mode of participation (task mode and/or relational mode). This conceptualization is further validated through an empirically-based user typology. Results of

cluster analyses identify a fourfold typology of user participation: hybrid-mode posting, task-mode posting, relational-mode posting, and task-mode lurking.

Drawing on Prentice et al.'s (1994) common-identity and common-bond framework, *Study Two* proposes and examines the group communication mechanisms through which members' OHC participation influences their perceived social support. Results of the SEM model suggest that two group communication mechanisms—identification with the community and interpersonal bonds with other members—mediate the relationship between OHC participation and perceived social support. Specifically, identification has a stronger mediating effect than interpersonal bonds. Furthermore, one-way ANOVAs reveal that identification, interpersonal bonds, and perceived social support vary across different user participation types (as identified in *Study One*).

A discussion of results is offered in addition to study limitations and future directions. Notably, this dissertation makes theoretical progress on the impact of different participation types and group communication mechanisms for benefiting members in OHCs. From an applied perspective, this research contributes to OHC design insights that can potentially (1) enhance users' participation in OHCs and (2) improve online intervention programs by targeting specific functions of OHCs.

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CHAPTER 1: INTRODUCTION

Online health communities (OHCs) such as PatientLikeMe (www.patientslikeme.com), Inspire (<https://www.inspire.com>), HealthBoards (<http://www.healthboards.com>), and HealthUnlocked (<https://healthunlocked.com/>) have become widely-used resources for obtaining social support (Fox, 2011; National Cancer Institute, 2012; Rains & Wright, 2016; Walther & Boyd, 2002). In these communities, users have access to web- and/or mobile-based social support by interacting in dyads and/or groups using emails, instant messaging, forums, blogs, wikis, and social networking sites (Rains & Wright, 2016). As OHCs have become more prevalent, communication researchers increasingly are interested in assessing the degree to which OHC participation is linked to positive health outcomes (Rains & Young, 2009; Shaw, Hawkins, McTavish, Pingree, & Gustafson, 2007). An extensive body of literature has shown that participating in OHCs can alleviate stress and depression (Braithwaite, Waldron, & Finn, 1999; Lieberman & Goldstein, 2005; Wright & Rains, 2013) and improve quality of life and well-being (Lorig, Ritter, Laurent, & Plant, 2006; Rains & Keating, 2011; Turner, Grube, & Meyers, 2001).

While there has been a substantial body of research published on OHC participation and social support, important gaps still remain, which could explain mixed results and disjointed understandings. First, the majority of existing studies have been conducted in structured group interventions where conversations were moderated by health professionals or confederates. Little is known about participation and health

outcomes associated with organically formed OHCs that fully rely on users' voluntary contributions. Second, OHC participation is almost always understood in terms of frequency of use and lacks a framework to identify different patterns of participation that more precisely capture *how* people use OHCs. Third, group communication is integral to creating and sustaining any given OHCs (Cline, 1999; Wright & Bell, 2003). Considering that OHC participation emerges from and is constituted in group communication (Poole, 1998), there is little understanding of group communication mechanisms that underpin the relationship between OHC participation and social support outcomes.

In this dissertation project, I conduct two interconnected studies to address the above gaps. *Study One* develops a measurement of OHC participation by creating a theory-based typology. I conceptualize and assess OHC participation along two equally important dimensions: level of participation (ranging from complete lurking to active posting) and mode of participation (task mode and/or relational mode). This conceptualization goes beyond the traditional measures of frequency to include users' objectives for participation. Then, for *Study Two*, building on the results of *Study One*, I draw upon the common-identity and common-bond approach (Prentice, Miller, & Lightdale, 1994) to propose and test a theoretical model that explains how two group communication mechanisms—identification with the community (Cheney, 1983; Hogg & Turner, 1987; Tajfel & Turner, 1986; Scott, Corman, & Cheney, 1998) and interpersonal bonds with other members (Wasserman & Danforth, 1988; Namkoong et al., 2012)—

mediate the relationship between users' OHC participation and their perceived social support.

Toward this objective, I employ a two-step study design focused on breast-cancer-patient participants who use OHCs. Step one involves an observational study and a pilot study using a convenience sample of breast cancer patients to evaluate the feasibility and statistical variation of four key constructs of this study: OHC participation, identification with the community, interpersonal bonds with others, and perceived social support. In step two, I conduct a survey of 371 breast cancer patients across 12 OHCs. This method helps me generate insights beyond isolated, single-community glimpses, and provide a new way to understand the variation in OHCs. Together, the two-step design contributes to the understanding of the process of group communication and social support outcomes associated with OHC participation. The following section provides rationales for the two studies.

Study Rationale

In this dissertation, I refer to “online health communities” (OHCs) as *any virtual space where people initiate, participate, and develop computer-mediated interactions to converse, exchange health-related social support, and seek beneficial outcomes in personal health*. These communities function as virtual collectives of users who engage in ongoing communication around a shared purpose, interest, or need over time, with most of the communication being text-based and technologically-mediated (boyd & Ellison, 2007; Porter, 2006). A variety of information and communication technologies

support interactions occurring in OHCs, ranging from email lists to instant messaging, forums, blogs, wikis, and social networking sites (Eysenbach & Köhler, 2002; Houston & Allison, 2002; Lacoursiere, Knobf, & McCokle, 2005; Greene, Choudhry, Kilabuk, & Shrank, 2011; Greene, Sacks, Piniewski, Kil, & Hahn, 2013). These online tools can quickly connect people, forming niche communities that house exchanges of social support (Chuang & Yang, 2012) and benefit users' overall health (Johnston, Worrell, Di Grangi, & Wasko, 2013).

Although the links between OHC use and important personal health outcomes are now well documented (for reviews, see Rains & Wright, 2016), disjointed findings and mixed results still exist concerning user participation and social support outcomes. First, the single-item measurement of OHC participation is problematic. Most existing studies have used "frequency of use" (i.e., login in times) or "intensity of use" (i.e., number of messages posted) to assess users' participation. Despite users' diverse participatory behaviors driven by various motives (Lampe, Wash, Velasquez, & Ozkaya, 2010), there is no theoretical framework to identify different participatory patterns more precisely. Second, researchers still know little about the specific ways in which social support processes are carried out in users' participatory behaviors or the role that different group processes play in the development and mobilization of online social support. Despite the importance of the participation-social support link, few studies have investigated potential communication mechanisms underpinning this process/relationship. To address

these gaps in the OHC literature, I conducted two interconnected studies that are introduced below.

Study One

The main objective of *Study One* is to develop an empirically-based OHC participation typology that can be used to (1) identify and describe distinct user types and (2) go beyond the traditional measures of time (i.e., frequency of participation) to include *how* people use OHCs (i.e., the goal and objective of OHC participation). As suggested by Johnson and Kulpa (2007), typologies in general, “reflect theoretical assumptions about, and conceptual organization of, the salient features of complex behavior” (p. 773). Typology development allows researchers to classify a wide assortment of facts and speculations into a more meaningful and manageable set of types (Bartol & Bartol, 2004). Such classification permits exploring the nature and consequences of different participatory behaviors within OHCs. In this study, I conceptualize OHC participation in two equally important dimensions: participation level (i.e., posting vs lurking) and participation mode (i.e., task-mode and/or relational mode). Figure 1.1 visualizes the conceptualization of OHC participation.

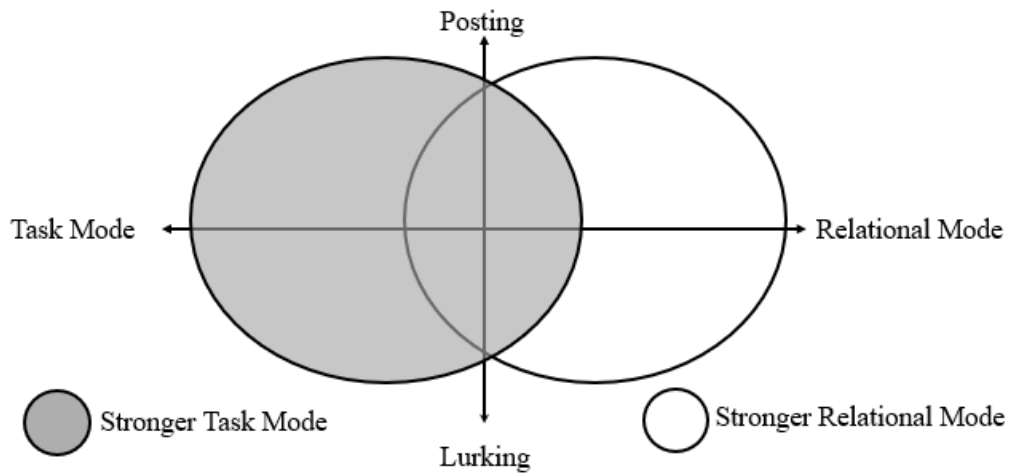


Figure 1.1. A *Conceptualization of Online Health Community (OHC) Participation Types in terms of Level and Mode*

OHC users' participation level (i.e., posting vs lurking) varies between two groups of users: posters and lurkers. Posters, also known as participants or contributors, tend to engage in online conversations by asking questions, commenting on others' questions, or replying to others' comments (Ridings, Gefen, & Arinze, 2006). In this study, I define posters as *users who maintain an active membership in at least one online health community and frequently post messages*. Lurkers, on the other hand, prefer browsing information to obtain the information they want but barely contribute to the community (Preece, Nonnecke, & Andrews, 2004). Given the active and goal-driven nature of information seeking, some scholars consider lurking as a peripheral form of participation (Nonnecke & Preece, 2003; Yeow, Johnson, & Faraj, 2006), while others describe them as "social loafing" (Kollock & Smith, 1996). In this study, I define lurkers

as users *who own an active membership in at least one online health community and never post a message.*

Prior research suggests that OHC users' participation mode might differ across two theoretical angles: task mode and/or relational mode (Beck, Paskewitz, Anderson, Bourdeaux & Currie-Mueller, 2017). Task and relational goals are the foundation of group interaction (Bales, 1950, 1954), which are pertinent to all forms of OHC interaction. In this study, task mode refers to *information seeking and information giving behaviors that drive subsequent community activities*, while relational mode concerns *the social fabric of online communities and development and maintenance of interpersonal relationship*. Task and relational modes are distinct, but they are also interdependent (Keyton, 1999; Keyton & Beck, 2009). For example, inherent in an OHC is the presence of other individuals with whom members often need to interact to accomplish a goal or perform a task. In doing so, members create or negate relationships with community members. Some users' participation may be primarily task-oriented (e.g., seeking surgery information), while other users' participation may exist mainly to satisfy relational needs (e.g., encouragement and empathy from similar others). Therefore, due to their interdependence with each other, task mode and relational mode are considered as two ends of a continuum rather than as mutually exclusive, as shown in Figure 1.1.

Study Two

After achieving a more precise identification of various participation patterns, the second study attempts to provide a theoretical framework for examining the relationship

between OHC participation and perceived social support—a fairly robust predictor of beneficial health-related outcomes (Gruenewald & Seeman, 2010; Holt-Lunstad, Smith, & Layton, 2010; Uchino, 2009). I draw upon the common-identity and common-bond approach (Prentice et al., 1994) to propose and test a mediation model that explains how two group communication mechanisms—identification with the community and interpersonal bonds with others—influence the relationship between OHC participation and perceived social support. Figure 1.2 presents the mediation model. According to Prentice and colleagues (1994), OHC users’ participation may lead to two group communication mechanisms: common-identity groups (i.e., similarity-based categorical groups) and/or common-bond groups (i.e., interaction-based dynamic groups). The distinction between the two communication mechanisms manifests in two primary and competing approaches to the group studies: the group identification perspective and the individualistic perspective.

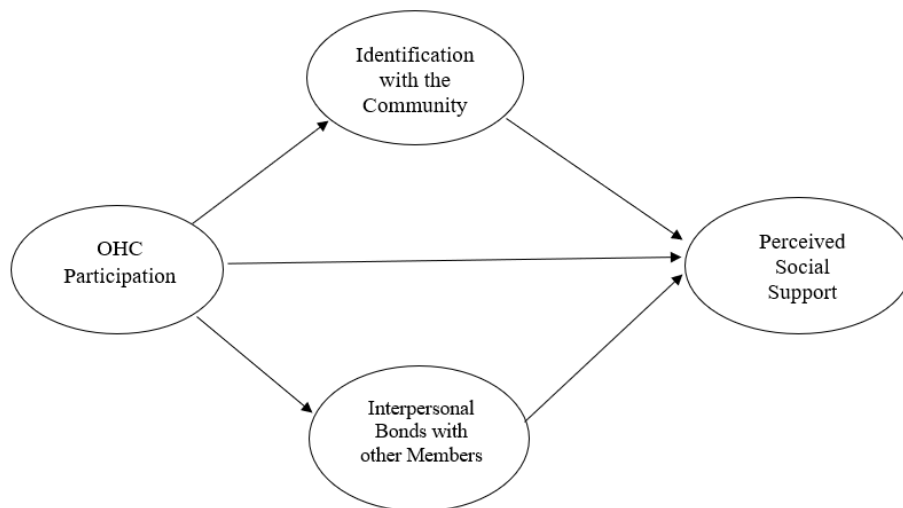


Figure 1.2. *Hypothesized Mediation Model*

One major school of thought defines a group as the manifestation of group identification. Ashforth and Mael (1989) define identification as “the perception of oneness or belongingness to some human aggregate” (p. 21). People typically have a sense of “we-ness” with a group or a community and feel connected with its purpose, character, or value (Cheney, 1983; Hogg & Turner, 1985; Tajfel & Turner, 1986; Stephens & Zhu, 2015). For example, members of a community choir (a voluntary leisure organization) may know few other members, but strongly identify with the cause endorsed by the choir and develop a sense of belongingness with the organization (Kramer, 2011; Meisenbach & Kramer, 2014).

Alternatively, the individualist perspective changes this definition by switching the attention from group identification to its individual members, implying that interpersonal relationships between and among members form the basis for groups. These relationships form bonding, whereby people feel affectively connected to and care for a community in which they are involved (Festinger et al., 1950). Interpersonal bonds can be deepened when personal identities are enacted through dyadic and/or group conversations, a situated activity that can shape close relationships (Wasserman & Danforth, 1988). For example, fraternity members feel attached to their fraternities in part because of the friendships they develop with other members by participating in multiple social events.

Taken together, *Study One* tackles the problematic measurement of OHC participation by classifying diversified online participation into meaningful categories. It

provides a theoretical framework that captures the richness of OHC users' participatory behaviors. Building on the assessment tool on OHC participation developed and verified in the first study, *Study Two* analyzes group communication mechanisms that are at the heart of OHCs. More specifically, it examines a theoretical model that explains the impact of users' OHC participation on their perceived social support through two mediators: identification with the community and interpersonal bond with other members. The next section discusses the significance of the two interconnected studies.

Significance

Given the importance and popularity of online supportive communication, this dissertation makes theoretical contributions to the interdisciplinary research areas of online group communication, social support, and health. It offers important insights about group communication mechanisms and intergroup relations within OHCs, making it possible to better understand the use and effects of contemporary forms of these communities for exchanging support and harnessing health benefits. Specifically, this project argues that the communicative mechanism of OHCs is more complex than simply providing a platform for members to ask for and provide social support. Rather, a constellation of individual, group, and contextual factors may facilitate or impede such efforts by shaping users' perceptions and outcomes of online supportive communication. More specifically, this study offers the first known study to outline a proposed typology that can be used to assess OHC users' participation; then, it develops and tests a mediation model to explain how OHC participation may predict users' identification with

the community and/or interpersonal bonds with others, and consequently influence their perceived social support.

Practically, this dissertation should provide guidance to many stakeholders involved in OHCs: users, community managers, designers, evaluators, and healthcare professionals. It informs different phases of the development of OHCs ranging from the design phase to the development, use, evaluation, and maintenance stages. The model developed here should be valuable especially for the study of communication challenges in OHCs, because it not only surfaces supportive communicative processes, but also examines the different user behaviors for getting involved in such processes. For example, this study can be useful in (1) strategically engaging users who have different levels of participation and (2) creatively designing identification-based and/or interpersonal bond-based communication features and activities that hold potential for benefiting users' health conditions. The prescriptive nature of the proposed mediation model can act as a powerful, yet parsimonious diagnostic tool for evaluating OHCs. Finally, even though the model is primarily focused on the context of health, I believe the underlying mechanism – involving input (participation), processes (identification and/or bond), and output (support outcomes) – is relevant and helpful for studies beyond health contexts. The following section further describes how this study unfolds.

Dissertation Outline

This dissertation proceeds in the following manner: Chapter 2 reviews the literature that informs this dissertation project. I start by reviewing previous studies on OHC to provide an overview of the current status of research in this area. Then, for *Study One*, I focus on summarizing and synthesizing literature that relates to typology development regarding online participatory behaviors. Next, for *Study Two*, I review theories and studies that support the hypothetical mediation model. I conclude this chapter with a list of theoretically-informed research questions and hypotheses for both studies.

In Chapter 3, I provide a detailed explanation of the procedures for data collection, operationalization of variables, and statistical analysis. Building on that, Chapter 4 contains the findings of the two studies using cluster analysis (*Study One*) and structural equation modeling (*Study Two*), respectively. In Chapter 5, I offer an in-depth discussion and interpretation of the findings, highlighting the theoretical and practical contributions of the typology development (*Study One*) and the mediation model (*Study Two*). Finally, I discuss limitations of this dissertation and propose directions for future research to continue exploring pertinent research on OHC.

CHAPTER 2: LITERATURE REVIEW

Online Health Communities (OHCs)

The existing literature regarding OHCs has provided insights into the current state of OHCs (e.g., Huh, McDonald, Hartzler, & Pratt, 2013; Wright, 2016), features and functions (e.g., Amsbary & Powell, 2012; Rains et al., 2015), health-related benefits (e.g., Batenburg & Das, 2015; Houston, Cooper, & Ford, 2002), and challenges associated with OHCs (e.g., Rains & Wright, 2016; Wang, Zhao, & Street, 2017). In this section, I review and synthesize empirical studies examining the use of OHC for acquiring social support and the outcomes of support. I conclude with two major lines of research that jointly inform the two studies conducted in this dissertation project.

The Current State of OHCs

The Internet has become an indispensable part of the landscape of supportive communication and health. It is revolutionizing how social support is exchanged and perceived, making OHCs one of the most exciting research areas in health communication and informatics. Based on the latest nationally representative survey, about 72% of Internet users in the U.S. searched health information online in 2012, and 16% have gone online to find others who have experienced similar symptoms (Fox & Duggan, 2013). For instance, people with chronic or life-threatening diseases use online resources to obtain information about their condition and ways to cope with it (Karnilowicz, 2011). In addition, Internet users are not solely passive consumers of online health information; they are also active producers (Nath, Huh, Adupa, &

Jonnalagadda, 2016). The massive amount of content they create and share on OHCs has the potential to reach millions of people (Fox, 2011).

The increasing popularity of OHCs is driven by a revolution in the current healthcare system from a reactive and “disease-centered” to a proactive and “patient-centered” approach (Lejbkowitz, Caspi, & Miller, 2012). Coined as personalized and participatory healthcare, this change in the healthcare system aims to leverage advanced healthcare technologies and encourage patients to become full partners rather than passive recipients in the healthcare decision-making process (Hood & Auffray, 2012). This notion of personalized and participatory healthcare empowers health consumers to be actively involved in their care and perform activities to achieve their health goals (Chen, Mullins, Novak, & Thomas, 2016; Samoocha et al., 2010). At the same time, empowered health consumers tend to take an active role in exchanging social support using OHCs (Oh & Lee, 2012).

OHCs are a specialized subset of online communities that share similarities with other online communities (e.g., financial consulting, gaming, brand loyalty). Generally speaking, online communities enable large, geographically dispersed groups of individuals to converse and enhance common interests (Wasko & Faraj, 2005). Users can build and maintain interpersonal relationships and create a supportive network of knowledge, ideas, and interpretations (Chiu, Hsu, & Wang, 2006; Herring, 2008). However, OHCs differ from other online communities due to the uniquely personal nature of healthcare management (Barack et al., 2008). The unique health context

contains information that matters for life or death. With that in mind, research on OHCs starts from the fundamental understanding of online information seeking and sharing behavior (Coulson, Buchanan, & Aubeeluck, 2007; Nambisan et al., 2011), computer-mediated support groups (Han et al., 2012; Han et al., 2014), and beneficial health outcomes (Batenburg & Das, 2015). With thousands of people logging on to share side effects, treatment options, test results, and coping strategies, OHCs have created an online archive for informed decision-making and patient empowerment (Johnston et al., 2013).

Features and Functions of OHCs

Community design influences the ways in which users can engage with others (Donath, 2007; Papacharissi, 2009). OHCs vary in terms of features and functions offered by different platforms (e.g., email lists, bulletin boards, social media). Some OHC studies have investigated social support exchanged across email lists and discussion groups (Braithwaite et al., 1999; Meier et al., 2007) and bulletin boards (Griffiths, Reynolds, & Vassallo, 2008). However, these earlier forms of OHCs lack some features of current social networking-based OHCs, particularly profile pages, friend networks, and location-based information. Recent research has offered insights on this trend of social networking sites (Chou et al., 2009; Hether, Murphy, & Valente, 2014; McLaughlin et al., 2012). For example, launched in 2011, *I Had Cancer* (www.ihadcancer.com) is a social networking platform for cancer fighters, survivors, and caregivers. This type of OHC offers convenient communication features that allow users to (1) create a personal profile page,

(2) find similar others in the same geographical area, (3) form and maintain an online friends network, (4) communicate through both public forums and private messaging, and (5) interact with others using rich media tools (i.e., combinatorial use of text, photo, video, audio, or other elements that encourage viewers to interact and engage with the content; McLaughlin et al., 2012).

With those features and functions, OHCs provide an extensive and diverse network of potential support providers who have relevant experiences and expertise (Wright, 2016). More importantly, compared to face-to-face interaction, seeking support from OHCs has a few advantages: (1) minimizing the embarrassment of disclosing stigmatized illnesses to others (Wright & Rains, 2013), (2) staying in an anonymous environment for accessing a diverse body of information and opinions (Rains & Young, 2009; Walther & Boyd, 2002; Wellman, 1997; Wills & Fegan, 2001), and (3) providing access to many forms of supports that are available all-day-every-day and do not require any travel (Eysenbach, 2003; Fogel, Albert, Schanbel, Ditkoff, & Neuget, 2002; Tanis, 2008a; Wright & Bell, 2003).

Various features and functions enable the mobilization of online social support. According to Cutrona and Suhr (1994), social support shared in OHCs can be classified into five different types: informational support (e.g., advice, guidance, or resources), emotional support (e.g., affection or sympathy), esteem support (e.g., compliments), tangible/instrumental support (e.g., food, transportation, money, or assistance with tasks), and network support (e.g., companions). Of the five types of social support, Braithwaite

et al. (1999) found that emotional and informational support are the most frequently offered support in an online health community for disabled patients, whereas network support and tangible aid are least frequently offered (Braithwaite et al., 1999). More recently, Rains and colleagues (2015) conducted a meta-analytic review of content analyses examining support messages shared on OHCs. They found informational and emotional support messages are most prevalent compared to other types of support messages.

Health Benefits of OHC Use

Researchers from a variety of academic disciplines have paid considerable attention to the relationship between social support processes and health outcomes (Bolger, Zuckerman, & Kessler, 2000; Eysenbach, 2003; Rains & Wright, 2016). At the most general level, there is evidence that simply participating in an OHC can be beneficial (e.g., Houston et al., 2002; Lieberman & Goldstein, 2006). Supportive interactions play critical roles in both psychological and physical health and well-being (Yoo et al., 2014). Specifically, communication researchers have contributed to a broader understanding of social support processes by examining how characteristics of supportive messages lead to positive reappraisals and coping behavior across a variety of health conditions, such as cancer, obesity, and HIV/AIDS (Braithwaite, et al., 1999; Query & Wright, 2003).

Participating in OHCs provides individuals with access to social support that ultimately improves health-related outcomes. For example, Pennebaker and Chung

(2011) found that posting personally traumatic experiences can have a range of psychosocial benefits. The self-reflexive process online can empower patients with increased feelings of competence, strength, independence, and help them feel less isolated (Han et al., 2011; Pennebaker & Chung, 2011). Similarly, Wright (2000) found that the amount of time a person spent communicating within OHCs is positively related to people's satisfaction with the support provided in OHCs. The benefits obtained from OHC participation, in turn, serve as the main drivers of continued participation (Fang & Neufeld, 2009; Joyce & Kraut, 2006).

Two general models offer insights on the positive health-related outcomes of OHC use: the main-effect model and the buffering model (for a review, see Cohen & Wills, 1985; Lakey & Cohen, 2000). The main-effect model focuses on the possibility that social support can have positive effects by directly improving one's coping resources. For example, receiving advice or empathy can help a support seeker better manage a stressor (e.g., a terminal disease). On the other hand, the focus of the buffering model is perceived support availability—the knowledge people have regarding available social support. Such knowledge affects support outcomes by influencing one's appraisal of a stressor. In other words, perceiving that one can gain access to supportive others may make stressors appear less severe and more manageable than if such resources are not available.

There is evidence that both receiving support in OHCs and perceiving support to be available are consequential for well-being. For example, based on a web-based OHC

called CHESS (Comprehensive Health Enhancement Support System), Gustafson and colleagues (1994) found that received online support improves quality of life and cognitive functioning and reduces healthcare costs and hospitalizations for users facing HIV/AIDS. In another study, Farnham et al. (2002) show that the use of an OHC helps to buffer the detrimental effects of stress in times of social isolation. Moreover, Rains and Young (2009) conducted a meta-analysis of 28 studies examining the health-related outcomes associated with people's participation in highly structured OHC interventions. They found that general OHC use leads to increased social support, decreased depression, enhanced quality of life, and improved self-efficacy for self-management.

Furthermore, OHCs also provide opportunities for users to be supporters, which may lead to psychosocial benefits. This phenomenon, also known as the "helper therapy principle" (Riessman, 1965, p. 214), has been supported by a few studies. For instance, Schwartz and Sendor (1999) discovered that supporters improve their psychosocial role performance (e.g., social activity), adaptability (e.g., self-efficacy function), and well-being (e.g., depression) even more than the supported patients. Similarly, in a nationwide survey of elderly people, providing support to an informal social network has been linked with feelings of personal control and lower levels of depressive symptoms (Krause, Herzog, & Baker, 1992). Similarly, a peer support study among abused women suggests that the ability to give support is associated with the supporters' own recovery (Henderson, 1995).

Challenges Faced by OHCs

In the past two decades, hundreds of OHCs have emerged (Fox, 2011; Rains & Wright, 2016). Many of those OHCs continue to exist and thrive today and their membership has grown (e.g., WedMD, Inspire). Other OHCs garner little participation from their users and some of these sites have disappeared completely. Aligned with the study rationale (see Chapter 1), I identify two major challenges faced by OHCs: participation and health outcomes. Neglecting these two challenges lessens an OHC's chances of becoming a sustainable community, one where members participate actively, meet their social support needs, and improve health conditions. Below, I articulate each challenge.

Participation. One challenge faced by OHCs is associated with attracting and maintaining participation (Iriberry & Leroy, 2009). In this era of participative media, users' voluntary participation is crucial for the success, survival, and contribution of any online community. Online communities need to rely on members' continued voluntary participation in order to remain as sustainable entities (Butler, 2001). Some online communities lose momentum and begin to die when they face poor participation, lack of quality content, unorganized contribution, and transient membership (Jarvenpaa, Knoll, & Leidner, 1998).

Participation is the lifeline of any online community. Researchers have argued that participation is fundamental for community members to develop a sense of belongingness, provide support to others, receive feedback, form interpersonal bonds, and

gain recognition for their contributions (Fiedler & Sarstedt, 2014; Ridings & Gefen, 2006). It is widely agreed that the larger the volume of messages posted and the closer members feel to each other and/or to the community as whole, the more successful the online community becomes (Iriberry & Leroy, 2009). These dimensions serve as basic building blocks for understanding and even solving the challenge of participation.

As a specialized subset of online communities, OHCs are faced with similar challenges on participation. To date, most studies conducted in the context of OHCs have been situated in highly structured formal groups, which means users' participation (i.e., online interaction) is mostly scheduled, required, and moderated in an interventional environment (Han et al., 2014; Huh et al., 2017; Rains & Wright, 2016). In these structured groups, moderators asked participants to briefly introduce themselves and engage in group discussions, which may be considered as “mandatory” rather than “voluntary.” One advantage of these structured intervention groups is that researchers can analyze users' action by tracking server log data rather than collecting self-reported data (Boase & Ling, 2013). However, it is both theoretically and practically challenging to generalize the existing knowledges of those communities to the variety of informal and loosely structured OHCs (e.g., The Cancer Forum, Facebook support groups) — the focus of this dissertation project.

In contrast to structured community interactions, the development and success of organically formed OHCs solely rely on members' voluntary contributions. For OHCs, it is important to maintain a diverse pool of participants who engage in persistent

conversations, contribute new information, refute dubious information, and offer social support matching others' needs. Understanding these participatory behaviors is critical for (1) improving participation and retention and (2) increasing OHCs' usefulness in helping users gain optimal match with social support that caters to their needs (Rains & Wright, 2016; Wright, Johnson, Bernard, & Averbeck, 2011).

Health Outcomes. Another challenge is centered on the inconsistencies of research findings on the relationship between OHC participation and health outcomes. Despite the extensive evidence of health benefits associated with OHC participation (e.g., Houston et al., 2002; Lieberman & Goldstein, 2006), a few researchers have discovered potentially negative outcomes. For example, among individuals with visual impairment, negative associations are found between OHC participation and self-reports of physical well-being (Smedema & McKenzie, 2010). Likewise, a survey of support community members in the Netherlands shows a negative association between social coping and the total number of weeks that members spent in the community (Tanis, 2008b). In a study of mental-health communities, active participants fare better in terms of stigma recovery than lurkers (Lawlor & Kirakowski, 2014). Yet, the authors also found that the frequency with which all respondents visit the community is inversely associated with stigma recovery. Moreover, in a study on social networking sites, Kim (2014) found that users' received social support is unrelated to life satisfaction.

Researchers have found a range of reasons underlying the mixed outcomes of OHC participation. First, it is evident that incorrect or misleading information, member

conflict and disagreements, and the absence of physical connections with other members may have negative impacts on OHC users (Attard & Coulson, 2012; Barak, Boniel-Nissim, & Suler, 2008; Esquivel, Meric-Bernstam, & Bernstam, 2006; Han & Belcher, 2001; Malik & Coulson, 2010). Some users may find it difficult to handle situations when exposed to unpleasant stories (Barak et al., 2008). Being frequently confronted with negative stories from others may frighten patients and increase concerns regarding the illness. If these situations continue, users are inclined to eventually abandon the community for that reason (Sandaunet, 2008).

Second, based on the optimal matching model (Cutrona & Russell, 1990), Wright and Miller (2010) suggest that various forms of social support are differentially beneficial depending on support seekers' needs. OHC users may feel stressed, isolated, and frustrated when the support they received does not match their perceived needs (Figueiredo, Fries, & Ingram, 2004). Third, individual differences may influence the outcomes of OHC participation, such as health condition, health literacy, and the availability of offline support (Glanz et al., 2008). In these cases, users may find it hard to (1) engage in online conversations, (2) build relationships with other users, and (3) feel affectively attached to the community (Ren et al., 2012). For instance, Yoo and colleagues (2014) found that for those with higher emotional communication competence, providing emotional support has positive effects on their perceived well-being, while the same exchanges have detrimental impacts for those with lower emotional communication competence. Such experiences may deepen the already

isolated situation that many OHC users experience in everyday life, which can lead to decreased sense of well-being and quality of life.

Breast Cancer as the Contextual Focus of this Study

People's OHC use is often contingent upon their health needs and pertains to particular conditions (Sandaunet, 2008). An initiating health event, such as the diagnosis of diabetes or lung cancer, may influence an individual's use of OHCs (LaCoursiere, 2011). Therefore, in this dissertation project, I situate the challenges of OHCs particularly in the context of women facing breast cancer concerns.

Women are avid users of online media channels (Duggan & Brenner, 2013), including OHCs (Rodgers & Chen, 2005), and breast cancer communities ranked high in the frequency of active postings compared with other OHCs (Davison, Pennebaker, & Dickerson, 2000). This is a trend that has held true in recent years (Pew Internet and American Life Project, 2013). While members of OHCs for breast cancer are predominantly women, research suggests that both men and women use and contribute to the communities (Abramson, Keefe, & Chou, 2015). Distinguishing breast cancer patients based on gender is beyond the analysis of this dissertation; thus, I primarily focused on breast cancer patients who currently use OHCs and identify themselves as women.

According to the most recent data, about 1 in 8 U.S. women will develop invasive breast cancer over the course of their lifetimes (American Cancer Society, 2018). Being diagnosed with breast cancer is a traumatic event that is both physically and mentally

challenging for any woman (Boehmke & Dickerson, 2006). They battle with physical concerns due to the disease and treatment (e.g., body images), while overcoming many psychological difficulties, such as distress, depression, and anxiety (Davis, Cohen, & Apolinsky, 2005). Research has found that newly diagnosed breast cancer patients may have high level of informational needs (Degner et al., 1997). They must make several major decisions on treatment within a short time frame. OHCs offer a convenient platform for them to ask questions and reduce uncertainties. At the same time, suffering may elicit people's intense emotions and hence their desire to vent to others and gain emotional support to help them better adjust to the disease. OHCs become a communal, safe, and non-judgmental virtual environment for breast cancer patients to provide and receive emotional support (Lieberman & Goldstein, 2006; Wen, McTavish, Kreps, Wise, & Gustafson, 2011).

Social support is a well-known factor in helping women fight physical and mental hurdles (Bloom, Stewart, Johnston, Banks, & Fobair, 2001; Trunzo, & Pinto, 2003). Social support groups/communities have been central to many psychosocial interventions for breast cancer patients, because they provide a confidential and welcoming atmosphere where patients can share their challenges and insights with each other (e.g., Han et al., 2012). Patients who participated in these interventions had lower cortisol levels, better immune system function and quality of life, and longer survival time (Classen, et al., 2001; Winzelberg et al., 2003). In addition to interventions, Wallner and colleagues (2016) found that following a breast cancer diagnosis, women who regularly use OHCs

are more likely to be satisfied with the treatment decision-making process, which contributes to their long-term recovery.

Thus far, I have provided an overview of existing research concerning OHCs and established breast cancer as the contextual focus of this dissertation project. The next two sections dive into the review of studies informing *Study One* and *Study Two*, respectively. Each study contains its own literature review and concludes with research questions and/or hypotheses for further statistical analyses.

Study One: Developing a User Typology of OHC Participation

As stated above, participation is crucial for the development and success of any OHCs. While extensive studies have examined OHC participation from different angles — such as antecedents and motives of participation, socialization, leadership, trust, and anonymity (Falisi, Wiseman, Gaysynsky, Scheideler, Ramin, & Chou, 2017; Fan, Lederman, Smith, & Chang, 2014) — participation is not defined or measured consistently across studies. Such inconsistency makes it difficult to (1) align identified antecedents with certain participatory behaviors and (2) draw conclusions regarding the impact of OHC participation on users' health-related outcomes.

Online participatory behavior is a complex activity that varies widely across individuals (Johnson & Kulpa, 2007). Often, prior studies have utilized limited measures of participation, such as counts of site visits, numbers of message posted, or pages viewed (e.g., van Varik & van Oostendorp, 2013; Wang et al., 2012). These measures are incomplete and lack a theoretical framework to capture the complexity of OHC

participation, which warrants more work in this area. In this study, I advance the conceptualization of OHC participation by defining participation in two equally important dimensions: level of participation (i.e., posting vs. lurking) and mode of participation (i.e., task mode and/or relational mode). This conceptualization is further validated through an empirically-based user typology. In the following section, I first review literature on user typology development of online communities in general and online health communities specifically. Then, I review theoretical frameworks that support the two-dimension conceptualization.

The Development of User Typology within Online Communities

A typology approach is useful to classify diversified behaviors into meaningful categories (Barnes, Bauer, Neumann, & Huber, 2007). This approach is not new in analyzing users' online participatory behaviors. Extensive studies have tapped into the categorization of user types based on their participatory characteristics and behavior (e.g., Brandtzæg & Heim, 2011; Kim, 2000). One line of research focuses on identifying social roles that users enact during online interactions. Researchers classify social roles primarily through ethnographic study of the network structure, behavioral patterns, and the meaning of interactions (Welser, Gleave, Fisher, & Smith, 2007). For example, Fisher and Durrance (2003) categorize online community users into two distinguishable social roles—information providers and information users. Turner and colleagues (2005) expand these categories by adding more user roles, including troll, spammer, binary poster, flame warrior, and conversationalist. Additional social roles are also identified,

including local experts, answer people, fans, and discussion artists (Burkhalter & Smith, 2003; Golder, 2003; Herring, 2004; Haythornthwaite & Hager, 2005). Table 2.1 provides a summary of different user categories developed by previous studies.

Table 2.1

A Summary of User Types of Online Communities

Authors	User Types
Brandtzaeg & Heim (2011)	Sporadics, Lurkers, Socializers, Debaters, and Actives.
Brush, Wang, Turner & Smith (2005)	Key contributor, Low volume replier, Questioner, Reader, and Disengaged observer
Fisher & Durrance (2003)	Information providers and Information users
Golder & Donath (2004)	Newbie, Celebrity, Lurker, Flamer, Troll, and Ranter
Kim (2000)	Visitors, Novices, Regulars, Leaders, and Elders
Kozinets (1999)	Tourists, Minglers, Devotees, and Insiders
Mathwick (2001)	Transactional Community Members, Socializers, Personal Connectors, and Lurkers
Nielsen (2006)	Lurkers, Intermittent, and Heavy Contributors
Turner, Smith, Fisher & Welsler (2005)	Answer person, Questioner, Troll, Spammer, Binary poster, Flame warrior, and Conversationalist
Waters & Gasson (2005)	Initiator, Contributor, Facilitator, Knowledge elicitor, Vicarious acknowledger, Complicator, Closer, and Passive learner

Another line of research applies a membership lifecycle perspective to identify user types. For instance, Kim (2000) describes how user types may evolve over time as

people's participation with the communities increases: from visitors to novices, regulars, leaders, and elders. First, "visitors" are those who are new to the community and unfamiliar with local customs, norms, and language. Then, after signing up for a community account, the next step is becoming a "novice" who still need to learn more about the community. Third, after getting more experienced in the community, the user turns into a "regular." Regulars have established reputations, know the environment and opportunities, and can communicate efficiently with other community members. Fourth, some regulars can take on leadership roles and be a "leader" to actively participate in community operations. Lastly, long-term members (including leaders) may become "elders" who "stepped down from their official roles" but still serve as "respected sources of cultural knowledge and insider lore" (Kim, 2000, p. 119). As Sonnenbichler suggested (2009), the five-stage model is not a linear process; instead, users may reverse the process and take on different roles. For example, when a leader loses interests in enacting leadership roles, they can become a "regular" and maintain an active role in contributing content. Or, they can become a "lurker," who is mainly interested in browsing content and finding the information they need.

More recently, Brandtzaeg and Heim (2011) outlined a user typology of social networking sites (SNSs) use to describe and distinct people's online participatory behaviors. They conceptualize SNS participation in terms of level (i.e., high vs. low) and objective (i.e., information mode vs recreational mode). More specifically, they assess participation level by asking how often users posted text, image, and video. Regarding

participation objective, they asked questions related to informational mode (e.g., look for new information, discuss, and make appointments for meetings with others) and recreational mode (e.g., profile surfing, kill some time, and looking for a new friend). Using a survey data from 5,233 SNS users, they identify five types of SNS users: lurkers (people who use SNSs, but do not contribute or interact), sporadics (low level users), socializers (people who use SNSs mainly for social interaction with friends and family), debaters (people who use SNSs mainly for debating and discussion), and actives (people who use SNSs frequently for almost all purposes, such as socializing, debating, and contributing). This user typology demonstrates substantial differences in patterns of SNS use and qualitative aspects of participation in SNSs (e.g., entertainment use, instrumental use, and social use). However, recreational purpose, found among SNS users, may not be an appropriate mode for OHC users who are burdened with various types of mental and physical illness. Therefore, more OHC-focused scales should be further explored and tested.

The Development of User Typology within Online Health Communities (OHCs)

Most studies have conceptualized OHC participation equally as actual use and measured it using a single-item scale. For example, Wang and colleagues (2012) assessed participation by asking participants' self-reported time spent in an online community or communities in a typical week. This single-item measure provides a limited view of OHC participation. Only frequency (i.e., login times) and intensity (i.e., number of messages posted) can be potentially captured with this measure. Some studies operationalized OHC

participation in a more complicated way. Mo and Coulson (2010) asked participants four questions to measure participation: length of use (in months), days of use in an average week, hours of use in an average week, and amount of posts. Similarly, van Uden-Kraan and colleagues (2009) used three indicators to assess users' participation during the last four weeks: frequency of visit, length of visit, and amount of posts. Batenburg and Das (2015) extended this measurement by incorporating the impact of engagement level across various user activities (e.g., read posts from others, react on others' posts, start a new topic, or ask a question).

Other studies have adapted Ellison et al.'s (2008) measurement on Facebook intensity. The 8-item scale was developed to obtain a better measure of Facebook usage than merely frequency or duration indices. It first includes two traditional self-reported elements: the number of connections and the amount of time spent on Facebook on a typical day. Then, it asks a series of Likert-scale attitudinal questions designed to assess the extent to which participants are attached to the community emotionally and integrate community activities into their daily lives.

Despite previous researchers' efforts in conceptualizing and operationalizing OHC participation, users' participatory behavior is primarily understood in terms of frequency of use, length of use, and/or users' attachment to the community. Given the fact that people's online behavior is more complicated with varied use and forms of participation (Bishop, 2007; Rivera & Cox, 2016; Preece & Shneiderman, 2009), we still

lack a framework to identify various patterns of OHC participation. In this study, I fill in this research gap by developing a typology of OHC participation.

This study is not the first to advance the scientific understanding of user patterns of OHC participation. For instance, informed by Kim (2000)'s stage model, Nimrod (2012) extended the membership lifecycle perspective to OHC research. In a study on online depression support groups, Nimrod (2012) found that group members might experience four stages of participation: distressed newcomers, passive followers, active help receivers, and moving on-quitters. When group members first discover the content posted in the group and become a member, they are in stage one, "distressed newcomers." As new group members, they are less likely to post content due to unfamiliarity of group norms. In stage two, when members are more familiar with the group, they tend to be "active help receivers" or "passive followers." The "active help receivers" are those who actively engage in conversations, share content, and socialize with other members, while the "passive followers" are those who remain as lurkers. In stage three, group members are "relieved survivors," because their depression levels all decrease to some extent regardless of their participation level (i.e., active posters or lurkers). In the last stage, as veteran group members, when they start feeling better and need less support, they can either stay in the group as "active help providers" or abandon the group and become "moving-on quitters." Even though conducting a longitudinal study and positioning OHC users in terms of their member lifecycle are out of the current study's scope, it is important to incorporate temporal elements into the analysis, such as

length of membership, time per visit, total time spent in the community, and frequency of visit.

Aiming to illustrate users' needs and differences in OHC participation, Huh and colleagues (2016) develop four personas: caretakers, opportunists, scientists, and adventurers. Caretakers are altruistic and experienced OHC users who desire emotional support exchanges more than information seeking. Opportunists are those information seekers who are not interested in interacting with other members. Scientists are interested in scientifically accepted evidence, while adventurers care about information that might not have been approved by the scientific community. However, this categorization falls short in addressing the presence of lurkers whose OHC use is "invisible" almost all the time yet their OHC use generates a significant amount of community traffic and digital footprints (Golder & Macy, 2014). Moreover, in a study on a Weight Watchers Facebook page, Ballantine and Stephenson (2011) identify three types of users: passive recipients, active supporters, and casual browsers. Nonetheless, the authors fail to provide concrete definitions regarding each of those user types.

In the current study, I conceptualize participation by capturing the level of participation (e.g., active posting and passive lurking) and the mode of participation (e.g., post texts, images, or videos, update profiles, and organize community events) simultaneously. Incorporating both dimensions can help assess the increasingly complex participatory behaviors within OHCs. The following subsection elaborates on each dimension of OHC participation.

Level of Participation: Posting and Lurking

The ways individuals participate in OHCs vary greatly but can be conceptualized along a continuum of participation. On one end, online participation can be active, such as posting and responding to messages, answering questions, or organizing group events; on the other end of the continuum, participation can be passive, such as reading content (Butler et al., 2007). Due to the storage, indexing, and searchability of OHCs, information within the communities is available to both active posters (i.e., users who actively participate in online discussions by asking questions and responding to others' posts) and passive lurkers (i.e., users who only browse information but never contribute to the information pool).

Posting (or content provision) is arguably one of the most important behaviors performed by online community members, which is defined as an online behavior “by which a member contributes valuable resources in the form of posting information and/or knowledge for public consumption” (Bateman, Gray, & Butler, 2006, p. 986). It can take a variety of forms, such as starting a new topic thread, responding to other members' inquiries, providing useful information, or organizing community events. Extensive studies have identified a few motives underlying active posters' participatory behavior: to build interpersonal relationships, offer expertise, get emotional support, and be a group member (e.g., Lampe et al., 2010; Nonnecke, Andrew, & Preece, 2006; Tedjamulia, Olsen, Dean, & Albrecht, 2005). Given that participation is an ongoing process,

researchers have found that members' continued posting behavior is encouraged by receiving responses from the community (Burke, Marlow, & Lento, 2009).

While users' active participation is critical for an online community's survival and sustainable development, many users prefer lurking (Soroka, Ravid, & Rafaeli, 2004). A broadly cited definition of lurkers includes "anyone who reads but seldom if ever publicly contributes to an online group" (Nonnecke & Preece, 2003, p. 110). Nonnecke and Preece (2000) found that 90% of online community members restrict their participation to merely reading content. Similarly, according a Pew Research Center's report (2009) on online health information, only 6% of Internet users have posted comments, queries, or information on health-related matters in OHCs, while 41% of them have experience of reading health information generated by other users (Fox & Jones, 2009). More recently, other researchers find that about half of OHC users are lurkers (Batenburg & Das, 2015; Setoyama, Yamazaki, & Namayama, 2011).

There are two group of ideas behind online lurking behavior: social loafing and socialization (see Yeow et al., 2006). First, persistent lurking behavior is sometimes viewed negatively as social loafing or free-riding, which can be destructive to community development, because lurkers use community resources without giving it back to the group (Kollock & Smith, 1996). Alternatively, lurking behaviors can be categorized as an early socialization process, whereby members learn conventional styles, implicit norms, and explicit policies of an online community (Yeow et al., 2006). In the book *Digital Habitats*, Etienne, White, and Smith (2009) call lurking "legitimate peripheral

participation”, a crucial process by which communities offer learning opportunities to those on the periphery. Rather than a simple distinction between active and passive members, this perspective draws attention to “the richness of the periphery and the learning enabled (or not) by it” (Etienne et al., p. 9). Essentially, lurking behavior can be beneficial, because it serves as an initial step in members’ socialization process and prepares them for future participation, and perhaps more effective contribution. Once lurkers are sufficiently “socialized” in the community, they tend to “de-lurk” themselves by converting from a peripheral participant into an active participant, which is the most successful outcome for both the individual and online community (Yeow et al., 2006).

Participation inequality (e.g., posting vs lurking) is not new to the literature of online communities. And even within participations, their involvement in community conversations is often sparse and uneven (Brandtzaeg & Heim, 2011). Scholars from different disciplines have used various yet complementary theoretical angles in explaining why people show different levels of participation. First, there are two competing hypotheses: social enhancement (“rich get richer”) and social compensation (“poor get richer”). The social enhance hypothesis (Kraut et al., 2002; Valkenburg, Schouten, & Peter, 2005), sometimes referred to as “The Matthew Effect” (Merton, 1968), suggests that those with more offline resources are willing to engage more with others online in order to augment their total resources, such as the number of connections (Zywica & Danowski, 2008). On the other hand, the social compensation hypothesis (McKenna & Bargh, 1998) contends that those who lack offline resources tend to engage

in more supportive communication online to compensate for this disadvantage. Both hypotheses are rooted in a functional perspective which explains why people reach out to online communities as a rich resource for enhancing or compensating the status quo of online resource.

Alternatively, Bishop (2007) proposed a 3-level theoretical framework for understanding why members of online communities take a participatory action and some prefer being “lurkers.” He identified three interrelated psychological antecedents of people’s online participatory behavior: a desire to participate (level 1), values, attitudes, and interests associated with participation (level 2), and the belief in one’s capabilities of contributing content to the community (level 3). The 3-level framework is consistent with findings from several qualitative studies that investigated reasons underlying users’ lurking behavior: (1) feeling that reading is enough to meet their needs, (2) thinking that they should get to know more about the community, especially its norms and communication style, (3) believing the information they can potentially provide for the community is not helpful at all, (4) not liking the group dynamics or perceiving it as not matching their need, (5) having technical difficulties with the posting process, (6) being shy about posting, and (7) free riding anonymously (Fingeld, 2000; Nonnecke et al., 2006; Preece et al., 2004; Walther & Boyd, 2002).

Nonetheless, previous studies on OHC participation have mainly focused on posting. Indeed, there are only a handful of OHC studies that have specifically examined lurking behaviors (e.g., Han et al., 2015; Mo & Coulson, 2011). The over-representation

of descriptive and empirical studies focused solely on active posting creates the potential bias for assessing the health benefits associated with OHC participation. Within these limited studies, there are mixed findings regarding the benefits people achieved through lurking in OHCs.

In a study on online HIV/AIDS patient community, Mo and Coulson (2010) found that lurking can be as empowering as active participations, as some lurkers reported feeling more energetic than posters. Meanwhile, there are no significant differences between posters and lurkers in several psychological and psychosocial outcomes, including self-care, self-efficacy, loneliness, depression, and optimism. On another note, they also found lurkers received less social support and felt less satisfied with their relationship with other members. In a similar study examining the differences in empowerment between posters and lurkers in online cancer support communities, van Uden-Kraan and colleagues (2008) found that active participants reported greater psychological well-being than lurkers. Yet, lurkers achieved similar feelings of being empowered as posters had, such as “being better informed,” “feeling more confident in the relationship with their physician,” “improved acceptance of the disease,” “feeling more confident about the treatment,” and “enhanced self-esteem, increased optimism and control.”

In a longitudinal study of an online cancer support group, Han and colleagues (2015) found that lurkers did not differ from posters in their short-term (i.e., 6 weeks) psychosocial outcomes, but after 3 months, lurkers appeared to benefit more than posters

in terms of functional well-being, depression, and perceived social support. Based on the data collected from 99 users of online support groups for mental health, Lawlor and Kirakowski (2014) found that compared to lurkers, active posters achieved higher levels of recovery from self-stigma and increased likelihood to have sought formal support. However, this study is limited by its small number of participants ($N = 99$). Furthermore, Setoyama, Yamazaki, and Namayama (2011) conducted a web-based survey among members of four Japanese online breast cancer communities. They compared the differences in five support functions between posters and lurkers, including emotional support/helper therapy, emotional expression, conflict, advice, and insight/universality. The results show that emotional support/helper therapy and emotional expression were significantly higher among posters, while no significant differences were found in the other three types of support functions. Regarding satisfaction of OHCs use, they found that lurkers were less satisfied with received health information than active posters.

Mode of Participation: Task Mode and Relational Mode

OHC members' difference in participation aligns with their unique needs for social support. These needs are driven by various aspects of their health conditions, such as stages of illness (e.g., newly diagnosed vs settled in managing illness), complications, and preferences and philosophies toward approaching the illness (LaCoursiere, 2011). Given the differences in needs, some users may just want to get quick answers to their questions, while others may need someone to chat with and build close relationships (Chiu et al., 2006; Wasko & Faraj, 2005). Based on Keyton (1999)'s work on group

communication mechanisms, those differences in participation are reflected in two primary modes of group/community life: task mode and relational mode.

A basic definition of group communication states that groups are comprised of interdependent members united by a common goal or purpose (Beebe & Masterson, 2012; Rothwell, 2013). This goal may take many forms and can vary on a spectrum ranging from more task-oriented modes to more relationally-oriented modes. Groups face an equilibrium problem where they have to manage tasks and relational goals (Bales, 1950, 1953). In the context of OHCs, it is important to consider (1) the task mode concerned with providing or receiving information, opinions, and suggestions, and (2) the relational mode concerned with solidarity or antagonism, agreement or disagreement, and tension release or tension.

Regarding task mode, the objective of people's OHC participation is to fulfill specific instrumental goals (e.g., relieve concerns on side-effects, make the best decision) in which the objective of participation is to seek for information. They are more interested in completing the necessary task, or series of tasks, to find step-by-step solutions required to meet their goals (Hirokawa & Salazar, 1999; Strijbos, Martens, Jochems, & Broers, 2004). When completing those tasks, OHC members are interdependent and coordinate their efforts to accomplish different goals. They oftentimes participate in dyadic and/or group discussions and post task messages that often focus on what group members know, what group members can do, or what level of effort they can or will expend. In essence, community formation and individual engagement do not need

to be based on social relations but can be more related to the common interests and special knowledge of the participants (Huang et al., 2009).

For relational mode, the objective of people's OHC participation is to support and motivate others. They are more interested in enacting relational roles that include encouraging, harmonizing, and compromising, along with engaging in gatekeeping, standard setting, observing, and following behaviors. As Keyton (1999) defined, "...relational communication in groups refers to the verbal and nonverbal messages that create the social fabric of a group by promoting relationships between and among group members. It is the affective or expressive dimension of group communication, as opposed to the instrumental, or task-oriented, dimension (p. 192)." OHCs are inherently social support groups that are contextually situated and socially sustained by the interpersonal and intragroup relationships developed by members through their online interactions (Hether et al., 2014; Keyton & Beck, 2009). Relational-mode communication in this way can make an individual feel either loved, esteemed, accepted, valued, or motivated, which ultimately creates an intense cohesiveness among group members (Teoh et al., 2009).

Taken together, both participation modes are valid and equally useful ways of online interaction but serve different purposes. An individual with stronger task mode tends to focus on "getting things done" efficiently and is less focused on developing and maintaining interpersonal relationships with the other users (Scheerhorn & Geist, 1997), whereas an individual who is relational-oriented focuses more on the relationship building. These participation modes are not mutually exclusive; OHC users can shift

from one to the other, although they may tend to go one way or another (Keyton & Beck, 2009).

Research Questions and Hypotheses

Based on the above review, it is possible that useful categories of OHC participation may emerge when discerning participation level (ranging from lurking to posting) and participation mode (task mode and/or relational mode) simultaneously. Results would benefit researchers and practitioners by providing information on participation patterns that are frequently encountered among OHC users. Therefore, I propose the following research question:

RQ1: Given that OHC users display different participation patterns in terms of level and mode, how can users be classified into meaningful categories or user types?

Study Two: Testing a Mediation Model

Social support is generally considered as a “protective” factor for people faced with health concerns (Albrecht & Goldsmith, 2003; Thoits, 1995). It is a coping resource from which people may draw when handling stressors (Thoits, 1995). Considerable research has focused on social support as a means to alleviate harmful effects of stress (Cohen & Wills, 1985; Underwood, 2000). Studies have repeatedly shown that social support exerts profound impacts on mental and physical well-being (see Rains & Wright, 2016 for detailed review). Feeling confident that social support will be available when needed (i.e., perceived social support) helps individuals cope more effectively with

stressful life events and appears to have long-term health benefits (Cohen & Syme, 1985).

OHCs have become a major source of social support for people with health problems. However, participation in OHCs doesn't guarantee that users receive the support they need or perceive the support is available during times of need. Some studies find that both posting and lurking in OHCs are predictive of social support (Houston et al., 2002; Mo & Coulson, 2011), while others find that active posting is not related to social support and even exerts negative impacts on users' mental health (Tanis, 2008b; Smedema & McKenzie, 2010). Scholars have contended that different "immersion" levels of OHC use can lead to mixed results of mental health, either beneficial or detrimental (Batenburg & Das, 2015; Rains & Wright, 2016). Such potential for OHC participation to be ineffective or even counterproductive points to the need for research that describes, analyzes, and explains the effects of various participatory behaviors. However, to date, little empirical efforts have been made to investigate mechanisms underlying the mixed findings between participation and support-related outcomes.

In this study, I argue that different group communication mechanisms may offer insights on the mixed findings. Previous studies have suggested that online community participation is realized through group communication, which accounts for the majority of users' personal experiences online (Gritsenko, 2016; Han et al., 2012; Ren et al., 2007). Group communication lies at the heart of OHCs and influences the way in which people experience and understand support-related interactions (Cline, 1999). Therefore,

investigating group communication mechanisms provides a basis for understanding the link between OHC participation and support-related outcomes. To that end, I draw upon the common-identity and common-bond approach (Prentice et al., 1994) to examine how OHC participation predicts two group communication processes —identification with the community and interpersonal bond with others — which in turn influence social support outcomes. The following section reviews theories and research that collectively support the model.

The Common-Identity and Common-Bond Approach

The idea of the common-identity and common-bond approach is: some group memberships are based on sharing a category membership (e.g., breast cancer survivor), while others are attracted by fellow group members (e.g., groups based on friendships). Based on this distinction, Prentice and colleagues (1994) identified two primary types of groups within which people may experience in-group/community interaction. This theoretical framework allows researchers to predict different functions that each group provides for its members as well as the different processes that occur within each group. *Common-identity groups* comprise individuals who ascribe group-defining characteristics to the self and to take the collective interest to heart (Turner et al., 1987). More specifically, members of common-identity groups are attracted to the group's norms, goals, activities, and other defining features. In contrast, *common-bond groups* comprise members who are attracted to one another as individuals. These two dominant group

perspectives pave the way for understanding communication mechanisms in OHCs. The next two subsections review literature on each perspective.

Identification. The theoretical perspective of common-identity group is rooted in the identification literature. According to Cheney (1983), identification with a social collective (e.g., company, virtual community) occurs when members see their own values or interests coinciding with those of the collective. This concept is consistent with social identity theory (SIT) and the related social categorization theory (Tajfel, 1982; Tajfel & Turner, 1979, 1986), which jointly explain people's tendency to classify themselves into many social categories. The premise of SIT is based on the "in-group" and "out-group" process of memberships. That means, depending on the group activities people engage in, group interactions can impact the "in-group" to which they belong and the "out-group" from which they are excluded. As explained by Hogg and Terry (2001), the two membership processes are synergized with two underlying socio-cognitive processes: categorization (which helps distinguish group boundaries and membership) and self-enhancement (where comparisons between salient groups serve to enhance the self by favoring one's own in-group).

Further, Cheney (1983) contended that identification occurs when people see themselves as group members of the same social category, share a sense of belongingness within a common definition of "we-ness", and achieve some amount of social consensus about the group and their membership. For example, an OHC can serve as a salient social category for many people's identity, especially those highly involved in the

process of exchanging social support, building ambient awareness of who knows what and who knows who, organizing community events, advocating opinions, and shaping community norms.

Based on a two-way thinking perspective, Cheney and Tompkins (1987) view identification as both product and process. As individuals and the collective (the collective can be an OHC as a whole or groups within an OHC) interact, a person's and the community's conceptualization of identity changes; identity, therefore, is created, transformed, and recreated through interaction. Scott and colleagues (1998) build on this perspective to argue that group identification is the process that teaches people the norms, values, and behaviors of a group. Group identification can reinforce an established identity and/or ultimately produce a new social identity, which is expressed primarily through language in our interactions with others (Scott et al., 1998; Scott, 2007).

Consistently, group identity is not only a key point of reference but also a practical building block for group-related objectives, activities, and projects (Scott, 2007). Groups can strategically use their established identity programs and identity messages—including values, norms, culture, ethics—to influence members' stances and behaviors (Stephens & Zhu, 2015). Thus, social collectives such as OHCs can potentially (1) leverage established norms and values to influence members' behaviors, (2) enhance attachment to the community, and (3) create new identities from group interactions.

Identification can be a major factor in comforting OHC users and giving them a feeling of relief. This general line of research suggests that the social context of OHCs,

with which individuals identify themselves, may exert influence over their perceived social support in response to stressful situations. Studies have shown that identification is a critical basis for social support that alleviates depression and stress (Branscombe, Schmitt, & Harvey, 1999; Haslam et al., 2005), benefits people's psychological and psychosocial health (Branscombe, Schmitt, & Harvey, 1999; Haslam et al., 2005), and boosts well-being (Crabtree, Haslam, Postmes, & Haslam, 2010).

Interpersonal Bonds. Interpersonal bonds, or human bonding, refers to the perception of a close relationship formed through supportive interpersonal communications among people who face similar concerns or problems (Namkoong et al., 2013). OHC members can achieve interpersonal bonds by providing support to others, especially when expressing emotional support (Namkoong et al., 2013). People cohere when they have mutual positive feelings toward one another (Lott & Lott, 1965). This interpersonal attraction provides basis for the development of human bonds and the formation of groups and group cohesiveness (Hogg & Turner, 1985).

According to the belongingness hypothesis, humans have a persistent drive to form a certain number of “lasting, positive, and significant interpersonal relationships” (Baumeister & Leary, p. 497). Bowlby (1969)'s attachment theory also posits that people's fundamental need is to form and maintain human bonds. Such attachment is well manifested in people's support-seeking behaviors (e.g., expressing distress or seeking comfort or assistance). When faced with stressful life events, people may treat other OHC users with whom they share strong interpersonal bonds as reliable attachment figures,

turning to and seeking contact with them. Many individuals participate in an OHC to reduce feelings of loneliness and social isolation (Barak, Boniel-Nissim, & Suler, 2008). Indeed, compared to other online communities built upon various purposes, OHC users have stronger desires to connect with similar others who are concerned and feel stigmatized (Batenburg & Das, 2015).

In comparison to the identification perspective, opportunities for self-disclosure and self-presentation shift researchers' attention from the group/community as a whole to individual members (Utz, 2003), who, online, are often represented by avatars, profile pictures, personal descriptions (e.g., age, gender, ethnicity, hometown, current residence), and personalized signatures (Postmes, et al. 2002; Ren et al., 2007; Sassenberg & Postmes, 2002). More recently, the inclusion of contact information such as phone numbers, email addresses, and instant messaging (IM) accounts enables members to connect and interact through multiple channels and become real-life contacts (Ren et al., 2007). These personalized options can signal a member's style, personality, and availability, while increasing the likelihood of interaction and bonding. Walther (2002) has discovered that the aggregated personal information available online promotes interpersonal bonds even among people who have not yet interacted. Two theoretical viewpoints can shed light on this phenomenon: bonding social capital and universality and similarity.

A perspective of bonding social capital. Building on a bonding social capital perspective, Putnam (Putnam, 1995, 2000) posited that interpersonal bonding emerges

from the relationships among members of a defined group (e.g., a self-help support community) and is positively associated with group cohesiveness— a crucial determinant of the positive psychosocial health outcomes associated with support group participation (Wasserman & Danforth, 1988). Similarly, Burt (2001) presented the idea of network closure as a proxy to interpersonal bonds wherein group cohesiveness is created through reciprocal ties among group (or network) actors. In Burt’s representation, interpersonal bonds are created through resource exchanges among setting actors wherein actors must adhere to setting norms. For example, OHC users may engage in private conversations with others and exchange support for meeting the specific needs of others, and these iterative support sequences may become a norm that favors interpersonal bonds.

A perspective of universality and similarity. In the specific context of social support, two concepts are closely related to the understanding of interpersonal bonds: universality and similarity. First, the perception of universality has been considered a primary benefit in support groups and requires commonality. A rationale for the perceived value of universality is the idea that individuals facing a similar stressor are in a unique position to understand one another in ways that one’s friends or family may not (Helgeson & Gottlieb, 2000; Rains & Young, 2009). Second, similarity is a natural product of the common practice of making interpersonal comparisons. People like others who are similar to them in preferences, attitudes, and values, and they are likely to work or interact with similar others (Byrne, 1997; Newcomb, 1961). In other words, an individual’s similarity to other people is a major determinant of his/her interpersonal

communication with them—the prerequisite of building interpersonal bonds.

Accordingly, sharing experiences with similar others who have the same problems, or simply knowing that others share similar problems, helps members feel less isolated (Shaw et al., 2000; Weinberg, Uken, Schmale, & Adamek, 1995; Zhang, et al., 2008). For example, in interviews with 13 prostate cancer patients who participated in a support group, Zhang and colleagues (2008) found seven participants (53.9%) mentioned they had experienced “bonding” with other group members, and that they value sharing their experiences with people with similar problems.

Without the presence of social cues – such as race, social class and lifestyles, and educational backgrounds – that normally influence the formation of interpersonal bonds in offline setting, OHC provides an ideal environment for users to form attachment and close relationship with each other. For instance, in Shaw et al.’s (2000) study on a computer-mediated social support (CMSS) group (a formal, highly structured OHC), participants credit other members as being in a unique position to understand and help provide support because they share similar problems and experiences. In addition, most participants have a desire to maintain intimate ties within the group, and these intimate relationships bring emotional benefits to group members. Therefore, due to the perception of universality and similarity, supportive communication in OHCs enables the formation of interpersonal bonds among participants. The perception of interpersonal bonds, in turn, likely plays a role in a variety of positive psychosocial health outcomes from OHC use.

Researchers have found that interpersonal bonds appear to have multiple and strong effects on people's emotional patterns and cognitive processes (Baumeister & Leary, 1995). According to past research conducted by the CHESS group, the level of support exchange and group cohesiveness is usually very high, leading many participants to stay in contact for years after the intervention ends. The interpersonal bonds formed and reinforced in this process lead to many lifelong friendships (Namkoong et al., 2012; Wen et al., 2011). Many of them even organize annual face-to-face meetings to maintain these bonds, which is believed to have profound impact on people's health and well-being (Wen et al., 2011). Conversely, lack of interpersonal bonding is linked to a variety of ill effects on mental health, adjustment, and well-being (Kawachi & Berkman, 2011).

Furthermore, Namkoong and colleagues (2013) found that interpersonal bond is a critical factor in influencing the coping strategies of breast cancer patients, and group participation is positively associated with perceived bonding. Providing emotional support to other members can improve interpersonal bonds. They argued that expressing emotional support is more powerful in promoting bond than receiving, because it fosters "a sense of trust in and commitment to other group members" (p. 173). From a reciprocal perspective, when OHC members feel they are capable of giving back to others in the community, they are likely to turn themselves from support receiver into support provider, which in turn, help form an interpersonal bond with other group members (Nimrod, 2012). However, this finding is limited in the context of structured social support groups where group interactions are typically moderated by health professionals.

In this study, I investigate OHCs that are solely based on members' voluntarily participation and lack of hierarchical structures (e.g., a moderator – member structure).

Perceived Social Support

At the heart of all studies of OHCs is the discovery and understanding of how supportive online interactions can effectively decrease stress level and bolster an individual's sense of well-being (Bertera, 2005; Goldsmith & Fitch, 1997; High & Dillard, 2012; Reinhardt, Boerner, & Horowitz, 2006). As a crucial indicator of one's well-being, perceived social support refers to the perception that assistance is or could be available from others (Albrecht & Goldsmith, 2003; Barrera, 1986; Goldsmith, 2004; Thoits, 1992). The perception of being cared for, whether or not this perception is accurate, can promote health (Wethington & Kessler, 1986). Indeed, researchers have suggested that the positive health outcomes may be linked to the perception of available support within OHCs rather than actualized support (Faber & Wasserman, 2002; Haines et al., 2002; Swickert et al., 2002). Multidisciplinary research has established that greater perceived support is associated with increased psychological and physical health (Cohen, 2004; Sarason et al., 1997). Perceived social support not only alleviates stress but also buffers the psychological effects of stress on health and well-being (Cohen & Hoberman, 1983; Cohen & Syme, 1985; Cohen & Wills, 1985; Haber, Cohen, Lucas, & Baltes, 2007; Rains & Young, 2009). In the context of cancer-focused OHCs, participants have reported (1) increased sense of social support, empowerment, and self-esteem, and (2) reduced level of stress, depression, cancer-related trauma, and social isolation (Fogel,

Albert, Schabel, Ditkoff, & Neugut, 2002; Lieberman et al., 2003; Im, Chee, Tsai, Lin, & Cheng, 2005; Rodgers & Chen, 2005; Winzelberg et al., 2003;).

In the current study, I chose perceived social support as the outcome of OHC participation for three main reasons. First, researchers have argued that perceived social support is a much stronger indicator in predicting people's psychosocial outcomes in OHCs than received social support (supportive actions received during times of need) and network position (the degree to which a person is integrated in a social network; Rains & Wright, 2016). Second, perceived social support reflects how OHC users consider themselves within a supportive social network (the number and strength of social ties). Such perception may indicate (1) the extent to which OHC users relate to the community and (2) whether they will continue using the community. Third, perceived social support is future-orientated and consistent with the on-going, open-ended nature of OHCs.

Research Questions and Hypotheses

Although it is not possible to attribute OHC users' perceived social support solely to participation and the associated two group communication mechanisms (i.e., identification and interpersonal bonds), it is plausible that these three factors can play a substantial role. The following sections present a series of hypotheses and research questions regarding the relationship between OHC participation, identification with the community, interpersonal bonds with other members, and perceived social support.

OHC participation → identification with the community → perceived social support. Community participation may have cognitive consequences that affect the

relative salience of social identities (Kramer, 2011; Meisenbach & Kramer, 2014; Scott, 2007). More specifically, engaging in OHC discussions, posting questions, and responding to others' questions may foster and reinforce identifications with the community. Certainly, one of the clearest points of integration between identification and computer-mediated communication has been looking at how social identities are socially constructed during online group interactions. As Postmes et al. (2000) argued, “[computer-] mediated groups can develop a meaningful and strong sense of identity through interaction” (p. 344). Some related works in this area have focused on how time spent in computer-mediated interactions can predict the emergence of new social identities related to that technology (Amaral & Monteiro, 2002). This identification process is constructed through online interactions and storytelling. Members tend to respond to others' posts using a collective “we” instead of “you” and “I”, which reinforces group identification and brings consolation (Wentzera & Bygholmb, 2013). Therefore, OHC participation may have a direct impact on users' identification with the community. The following hypothesis is posed.

H1: Users' OHC participation is positively associated with their identification with the community.

It is expected that when people identify with a community, they will see other in-group members as part of the self (rather than as external to the self); meanwhile, this sense of social categorization will motivate individuals to promote their own well-being and support others with useful forms of help. Identification with OHCs provides a basis

for interpreting the quality and quantity of available social support in a constructive way (rather than treating it with suspicion; Nadler, 2010). It is conceivable that when people identify strongly with the community, they are likely to view the community as a helpful resource from which they can draw positive support, particularly when facing health concerns. Thus, the next hypothesis in this study is posed:

H2: Users' identification with the community is positively associated with their perceived social support.

Scholars have agreed that one's social identity and social connectedness are closely related to their health (i.e., the social identity approach to health; Tajfel & Turner, 1979; Turner et al., 1987; Turner, Oakes, Haslam, & McGarty, 1994). Recently, Haslam and colleagues (2016) argued that "group ties are beneficial for health because they provide a basis for giving and receiving social support" (p. 245). Identification provides a solid theoretical perspective for how OHC participation may relate to members' perceived social support. Therefore, given the scholarship previously cited, the following hypothesized relationship is advanced:

H3: Users' identification with the community mediates the relationship between OHC participation and perceived social support.

OHC participation → interpersonal bond with other members → perceived social support. Participation may help members establish social ties and close bonds with others (Bagozzi & Dholakia 2002). Participating in OHCs is inherently "an interpersonal, transactional process" (Collins & Feeney, 2000; p. 1053) that involves

dyadic interactions between support seekers and providers. Online interactions — such as responding to others' posts — can (1) let the original poster know that people pay attention to his/her questions or comments, and (2) signal to others that the community is active, and members are open to form connections. It builds a strong case that these interactions may eventually build interpersonal bonds and make future interactions more sustained. Thus, the following hypothesis is proposed:

H4: Users' OHC participation is positively associated with their interpersonal bonds with other users.

An OHC member's assessment of his or her relationships with other members serves as a premise for creating, delivering, listening to, and interpreting online supportive communication (Beck & Keyton, 2014; Keyton & Beck, 2009). When people have stronger interpersonal bonds with others, they are likely to not only attribute validity and credibility to social support received but also perceive that social support is available during times of need. Consequently, it can be expected that strong interpersonal bonds with other members of the community boost posters' perceived social support. Therefore, the following hypothesis is proposed:

H5: Users' interpersonal bonds with other members are positively associated with their own perceived social support.

The immediacy and openness in sharing common concerns (e.g., treatment, medication) and personal details (e.g. body image, lifestyles) foster interpersonal bonds (Orgad, 2005). The formation of such close bonds in a short time and convenient way

attracts cancer patients to turn to OHCs for social support and new relationships (Beaudoin & Tao, 2007; Klemm et al., 2003). Given women affected by breast cancer may not have anyone within their personal networks who shares a similar experience, actively participating in OHCs may be linked to positive support outcomes due to new relationships formed through online interactions. This argument coupled with the previous literature on interpersonal bonds generates the next hypothesis:

H6: Users' interpersonal bonds with other members mediate the relationship between OHC participation and perceived social support.

Incorporating different user types in the mediation model. The final series of research questions focus on the relationship between participation types and perceived social support. Based on the typology development of *Study One*, various participatory patterns may lead to different group communication mechanisms and support-related outcomes. Therefore, I ask the following research questions:

RQ2: Following the results of the typology development, will the identified user types be significantly different from each other in terms of identification with the community?

RQ3: Following the results of the typology development, will the identified user types be significantly different from each other in terms of interpersonal bonds with other members?

RQ4: Following the results of the typology development, will the identified user types be significantly different from each other in terms of perceived social support?

Chapter Summary

This chapter first provides an overview of OHC research and synthesizes scholarship examining support seeking, health outcomes of acquiring online social support, and challenges faced by OHCs. Important questions remain about the conceptualization of OHC participation and broader communication mechanisms contributing to the support-related implications of OHC. This dissertation project—consisting of two interrelated studies—is a preliminary exploration of these questions. Table 2.2 presents research questions and hypotheses posed by the two studies.

Table 2.2

Summary of Research Questions and Hypotheses (Study One & Study Two)

RQ1	Given that OHC users display different participation patterns in terms of level and mode, how can users be classified into meaningful categories or user types?
H1	Users' OHC participation is positively associated with their identification with the community.
H2	Users' identification with the community is positively associated with their perceived social support.
H3	Users' identification with the community mediates the relationship between OHC participation and perceived social support.
H4	Users' OHC participation is positively associated with their interpersonal bonds with other users.
H5	Users' interpersonal bonds with other members are positively associated with their own perceived social support.
H6	Users' interpersonal bonds with other members mediate the relationship between OHC participation and perceived social support.
RQ2	Following the results of the typology development, will the identified user types be significantly different from each other in terms of identification with the community?
RQ3	Following the results of the typology development, will the identified user types be significantly different from each other in terms of interpersonal bonds with other members?
RQ4	Following the results of the typology development, will the identified user types be significantly different from each other in terms of perceived social support?

CHAPTER 3: METHOD

Study Overview

This dissertation project consists of two interconnected studies: the goal of *Study One* was to test a typology of OHC participation. The goal of *Study Two* was to examine a mediation model with identification and interpersonal bonds serving as mediators in the relationship between OHC participation and perceived social support. To address the research questions and hypotheses derived from both studies, I collected quantitative survey data by employing a two-step study design with OHC users facing breast cancer concerns. Step one involved an observation study and a pilot study that leveraged a convenience sample of 127 users of an OHC to examine the feasibility of the instruments and the proposed model that were further tested in step two—the primary study. After making changes to the instruments, I recruited 371 users of 12 OHCs for the primary study. This chapter describes the research site, data collection details for both the pilot and primary survey, and the operational details of each variable. This chapter concludes with the data analytic procedure.

Research Site

Research sites of this project were virtual environments where people seek and exchange social support regarding breast cancer. These environments served as a medium in sharing cancer information, forming and maintaining interpersonal relationships among breast cancer patients, survivors, and caregivers. To study these online environments, I collected data from 12 online health communities where breast cancer was listed either as the main topic or as a subsection. All of the communities were

powered by web- and/or mobile-based platforms. Users’ participation was organized in threads of posts. They could create their own profile and connect with similar others.

Table 3.1 summarizes the characteristics of OHCs in this study.

Table 3.1

Characteristics of Online Health Communities (OHCs) in this Study

Community Name	Platform	Format	Community Size
1. breastcancer.org – Breast Cancer Forum	Web-only	Forum	N/A
2. WebMD Breast Cancer Community	Web-only	Forum	N/A
3. Inspire - Advanced breast cancer support group and discussion community	Web-only	Forum	26491
4. The Cancer Forum – Breast Cancer	Web-only	Forum	56317
5. PatientsLikeMe - Real support for people living with breast cancer	Web & Mobile	Forum	5635
6. HealthUnlocked - Breast Cancer Haven	Web & Mobile	Forum	2004
7. Breast Cancer Support - I Got This!	Facebook (Web & Mobile)	Forum & Social networking	7531
8. Breast Cancer Integrative Healing {Integrative Tribe}	Facebook (Web & Mobile)	Forum & Social networking	2377
9. Breast Cancer Sisters Support Group	Facebook (Web & Mobile)	Forum & Social networking	9402
10. American Cancer Society – Belong	Mobile-only	Forum	N/A
11. Stupid Cancer	Mobile-only	Chatroom	N/A
12. ReachOut	Mobile-only	Forum	N/A

Note. The community size data was collected on February 1st, 2018. If the data was not available, I marked the community size as “N/A”.

In terms of community design, OHCs contained different types of users who had varying levels of access. For some communities, users could access community information without having an account. They were only required to create an account or login in an existing account if they participated in community activities, such as responding to others' posts, initiating a conversation, creating a subgroup, and following other users. Some communities were forum-based and had their own URL. Other communities were nested in popular social media sites, such as Facebook and Twitter, which means people had to have an active social media account to access any community information and activities.

Mobile platforms provided an alternative way to access OHCs. Many web-based OHCs (e.g., Facebook support groups and HealthUnlocked subgroups) have created mobile applications to allow their users instant and real-time access from anywhere they have access to the Internet. Additionally, native mobile-based OHCs were also available at the time of this study (e.g., Stupid Cancer and ReachOut), which allowed members to exchange social support by location-independent information and mobile access to existing community infrastructures.

For this study, I selected and contacted a total of 31 OHCs based on their popularity and prominent presence in search tool results. Since OHCs have a variety of community features and functionalities, studying a diverse body of OHCs should provide a comprehensive picture of users' participation. After negotiating access to those communities (see details of negotiation in the following section), I was allowed to recruit participants from the following 12 communities: breastcancer.org, WebMD, Inspire, the

Cancer forum, PatientLikeMe, HealthUnlocked, Cancer support group (Facebook), Breast Cancer Integrative Healing (Facebook), Breast Cancer Sisters Support Group (Facebook), Belong (mobile-only), Stupid Cancer (mobile-only), and ReachOut (mobile-only). The following section details the data collection procedure.

Data Collection Procedure

Pilot Survey

From December 2016 to May 2017, I first conducted an observational study on the breast cancer subgroup of one forum-based OHC called *The Cancer Forums* (<https://www.cancerforums.net/forums/12-Breast-Cancer-Forum>). Before collecting observational data, I consulted with the Institutional Review Board (IRB) at the University of Texas at Austin about this study. IRB confirmed that this observational study was exempt, because (a) the information of interest was already available on or via the Internet without researchers' direct interaction with human subjects, and (b) the collected information was not identifiable.

During my observation, I did not participate in any community activities because that would have required faking an illness which I believed to be unethical and could bias the study. Through observation of a total of 97 threads and 2115 posts, I took notes on patients' organic conversations, naturally occurring trends in social support (e.g., desires, symptoms, seemingly positive remedies), and other pieces of information that would not otherwise be revealed. I found that participants of the breast cancer group were actively posting messages and responding to peers, and the number of participants were increasing steadily. The information gathered this way offered insights on the

communication patterns, norms, and governance structures of the community and the role the online community played in the lives of its members.

Following the observational study, I submitted an IRB proposal to conduct a pilot survey within the same community. The cross-sectional survey was designed with questionnaire items that were validated in the prior literature. I used the pilot survey to identify if the proposed instruments were inappropriate, extraneous, or too complicated for the large-scale primary study (Baker, 1994; De Vaus, 1993; Fink & Kiseoff, 1985). After I obtained IRB approval, I posted a recruitment message that contained the URL of the web-based survey to the breast cancer community. Participants were informed about the voluntary nature of the survey, information being collected, and anonymous nature of data collection. I particularly highlighted that no personal identifiers would be collected or stored with the data.

To be qualified for the pilot study, participants had to be female, over 18 years old, and consider themselves as a user of *The Cancer Forums* at the time of this study. Participants accessed to a consent information page (Appendix A) that contains my university affiliation, research goals, and contact information. A reminder message was sent to the same community board every week from July 11st to September 10th, 2017. Ultimately, the call for survey participation resulted in a total of 127 participants over the course of a two-month period.

Participants who accessed the survey had an opportunity to enter their email address in a drawing for one \$20 Amazon.com gift cards. There were 42 email entries from the pilot survey, and the collected emails were saved in a separate file from survey

responses. After selecting the winner for the drawing, I erased the emails from both the online drive and the offline hard drive on which they were stored. Results of the pilot study are presented below.

Pilot Survey Results

During this time, 142 people started the online survey from July 11st through September 10th, 2017; however, after inspecting the data, 15 cases were removed from data analyses due to excessive missing data (only completed 2 questions out of 34 required questions). Most respondents were 20-60 years old, and the mean age was 37.2 years. About 91% of the respondents identified themselves as Non-Hispanic White, 4% as black or African American, and 2% as Asian, and 3% as multiracial or others. Most respondents (62%) were married, while 21% were single or divorced. Nearly half (49%) reported having annual household income from \$50,000 to \$74,999 and 35% reported income lower than \$5,0000. Regarding health, 59% perceived their health as very good or excellent, and only 19% perceived their health as poor or very poor. The results of the pilot study showed that the scales adapted from existing measures maintained their reliability (ranged from .77 to .90). Table 3.2 presents the scale reliabilities in the pilot study, and Table 3.3 presents correlations between the variables. See the primary study for detailed scale items and related statistical tests.

Table 3.2
Scale Reliabilities for Pilot Study

Scale	Number of Items	Cronbach's Alpha
Online Health Community Participation	26	.72
Identification with the Community	5	.87
Interpersonal Bonds with Community Members	3	.89
Perceived Social Support	29	.81

Table 3.3
Summary of Bivariate Correlations of Variables in Pilot Study

Variable	1	2	3	4
1. Online Health Community Participation	1			
2. Identification with the Community	.68**	1		
3. Interpersonal Bonds with Community Members	.41*	.46*	1	
4. Perceived Social Support	.40*	.28*	.29*	1

Note: N = 127. * $p \leq .05$ ** $p \leq .01$ *** $p \leq .001$

Primary Study Survey

After receiving IRB approval, I collected data through an online survey hosted by Qualtrics that was available from September 11th, 2017 to February 11th, 2018. To recruit participants, I contacted the administrators of 31 active OHCs communities and asked their permission to post a call for volunteers on their websites (See Appendix B). All communities as shown in Table 3.1 were English-based and had a section explicitly targeted people with breast cancer. Only 12 administrators approved, four said that they

would examine the request but never answered. Others did not respond even after multiple requests (up to 3 times). In each of the 12 communities with approval, I first created an account and then posted the recruitment message.

Specifically, I posted repeated recruitment messages to the following 12 communities: breastcancer.org, WebMD, Inspire, the Cancer forum, PatientLikeMe, HealthUnlocked, Cancer support group (Facebook), Breast Cancer Integrative Healing (Facebook), Breast Cancer Sisters Support Group (Facebook), Belong (mobile-only), Stupid Cancer (mobile-only), and ReachOut (mobile-only). For the six domain-specific communities—including breastcancer.org, WebMD, Inspire, HealthUnlocked, the Cancer forum, and PatientsLikeMe—I posted recruitment message directly to their breast cancer group. For the three Facebook communities, I used my personal Facebook account to post the recruitment message. For the two mobile-only communities (i.e., Stupid Cancer, ReachOut, and Belong), I first used my personal IOS device to download and install the applications, and then I posted related recruitment information.

For Facebook groups, I initially searched for the key word “breast cancer” using the Facebook search function, which resulted in 54 groups related to breast cancer. I then selected groups that met the following two criteria: (1) having more than 1000 members in the search results and (2) having at least five posts per day on average. Based on the criteria, 16 Facebook groups were selected and contacted. 15 of them were closed groups, which means only users who had been approved and/or invited to the community could see the content shared within it. Only one Facebook group was an open group, a group that anyone with a Facebook account could join or “like”. Those 16 groups were

launched between February 2007 and October 2014 and had more than 63800 members at the time of the study, which made them as legitimate communities focused on people with breast cancer or people who were affected by breast cancer. After negotiating access, I was able to post the recruitment message in two closed groups (i.e., Breast Cancer Integrative Healing {Integrative Tribe} and Breast Cancer Sisters Support Group) and one open group (i.e., Cancer Support Group).

In the end, a total of 371 participants completed the survey (see Table 3.4 for the demographics of survey participants). All participants were entered a drawing for ten \$20 Amazon gift cards. The raffle for being entered into the drawing had been closed as of February 10th, 2018. At the end of the anonymous survey, participants were asked to answer the question: “Do you want to receive the incentive?” If they answered yes, they were redirected to a separate survey where their contact information was collected. This way, the survey responses and the contact information were stored in two separate “pools” and were not linked to each other so as to keep survey responses anonymous. After the prizewinners were notified via email, all email addresses were deleted. The next section introduces data screening procedures to make sure my data set was clean and ready to be further analyzed.

Table 3.4

Demographic Information of Participants in Primary Study

Demographic	Frequency	Percentage
Age		
18-29	67	18.8%
30-44	132	37.1%
45-59	120	33.7%
60-65	26	7.3%
Over 65	11	3.1%
Ethnicity		
American Indian/ Alaskan Native	8	2.2%
African American or Black	42	11.8%
Non-Hispanic White	224	62.9%
Hispanic	36	10.1%
Asian/ Pacific Islander	51	14.3%
Marital Status		
Single	22	6.2%
Married	251	70.5%
Divorced	53	14.9%
Living with partner/significant other	32	9.4%
Highest level of Education Achieved		
Some high school or less	72	20.8%
Completed high school	53	14.9%
Some college/trade school	37	10.4%
Completed college	136	38.2%
Graduate school	58	16.3%
Annual Household Income		
Less than \$25,000	27	7.6%
\$25,000 to \$49,999	103	28.9%
\$50,000 to \$74,999	168	47.2%
\$75,000 to \$99,999	43	12.1%
\$100,000 or more	15	4.2%

Data Screening

Data screening is required before conducting any statistical analyses (Malone & Lubansky, 2012). Once data were collected and exported from Qualtrics, I screened the data to ensure no violation of the statistical assumptions of SEM and cluster analysis, which included accuracy of data, missing data, outlier, homoscedasticity, linearity, multivariate normality, and multicollinearity. All descriptive analyses and data

preparation for SEM and cluster analysis were performed in IBM's Statistical Package for Social Sciences (SPSS) 24. Model specification and evaluation were executed using Mplus 7.2 (Muthén & Muthén, 2012). Below, I explain each of the statistical assumptions along with the method used to verify that the data met each prerequisite for analysis. Discovery and handling of problematic items are also discussed.

Accuracy of Data

To ensure data accuracy, I took the following steps. First, the online survey system automatically stored survey responses in online databases which effectively eliminated problems related with imputing data from paper-and-pencil self-administered survey (Van den Broeck, Cunningham, Eeckels, & Herbst, 2005). Second, given the complexity and length of the survey, illogical or inconsistent responses caused by respondents' carelessness or fatigue were likely to occur. I used one set of attention checks (also known as instructional manipulation check) to assess whether participants were paying attention to the instructions. The stem of the manipulation check reads: "For the next set of questions, please choose response 4 when prompted." Respondents who did not choose 4 were further scrutinized to decide whether their responses were reliable enough to be retained in the sample. Third, I also screened survey completion time to screen data (Malhotra, 2008). It is highly unlikely for an attentive participant to complete a survey of more than 70 items within a minute. Therefore, a response was considered to be lacking in validity and accuracy if it was completed in a suspiciously short time. In this study, eight participants were found to be excessively careless and thus excluded from the sample. After making this change, the sample size is 363.

Missing data

I checked the completeness of all survey responses. Missing data was examined to determine whether the remainder of information was usable. I employed mandatory responses for 30 items in the online survey, so it was not unexpected that missing values were relatively lower than online surveys that did not require mandatory responses. In this study, there were 51 missing cases in this study, accounting for 9% of the overall data. As Rubin (1976) stated, data could be missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR). Without appropriate treatment, missing data can potentially lead to misleading inferences (McKnight et al., 2007). I used missing value analysis in SPSS 24 to identify the missing data mechanism. Little's MCAR test (Little, 1988) resulted in a statistically significant value, $\chi^2(14,417, N=363) = 926.19, p < .001$, suggesting the data were not missing completely at random (MCAR). In other words, the data were either missing at random (MAR) or missing not at random (MNAR). Scholars have suggested that when the amount of missing data is small (i.e., 10% or lower), typical missing data handling procedures — such as listwise deletion, pairwise deletion, mean substitution, and expectation maximization (see Little & Rubin, 2002; Roth, 1994; Schafer & Graham, 2002) — tend to generate similar results (Hair et al., 2010; Tabachnick & Fidell, 2012). For this study, I chose to use expectation maximization because it retains the original sample size and provides accurate standard errors (Schlomer, Bauman, & Card, 2010).

Outliers

Both univariate and multivariate outliers were examined. Theoretically speaking, a univariate outlier is an observation with an extreme value on a single variable, while a multivariate outlier is a case with a combination of extreme values on two or more variables (Hair et al., 2010). The presence of these outliers can affect statistical analyses, distort the representativeness of the sample, and cause Type I and Type II errors (Tabachnick & Fidell, 2012). For univariate outliers, Iglewicz and Hoaglin (1993) suggest cases with an absolute z score higher than 3.5 be labeled as potential outliers. Following their suggestion, I found no univariate outliers in the sample. For multivariate outliers, I used the Mahalanobis distance to label potential outliers. A case with Mahalanobis score larger than 21 was considered as a multivariate outlier and should be removed from the study. Following this rule, seven cases were removed, resulting in a sample of 356 for the subsequent analyses.

Linearity

The assumption of linearity holds that the relationship between the independent variable (IV) and the dependent variable (DV) is linear. If this relationship becomes non-linear, the results of the regression will underestimate the true relationship, while carrying two risks: increased chance of a Type II error for the IV, and in the case of multiple regression, an increased risk of Type I errors (over-estimation) for other IVs that share variance with that IV. To check for assumption violation, I used a bivariate scatter plot of residuals (i.e., plots of the standardized residuals as a function of standardized predicted

values). The scatter plot followed a linear pattern, so I ruled out any violation of linearity within the data.

Homoscedasticity

Homoscedasticity in a data set assumes the variance of errors is the same across all level of independent variables. I checked this assumption by plotting the standardized residuals (the errors) by the regression standardized predicted value. The resulting plot showed that the residuals were normally distributed, and variances were uniform across all levels of the independent variables. Thus, heteroscedasticity was not an issue with my data set.

Multicollinearity

Multicollinearity occurs when two or more of the independent variables are highly correlated (Bollen, 1989). As suggested by Kline (2011), multicollinearity causes Type II errors by inflating the size of standard errors, which can be especially problematic when running SEM models for the current study. To check the presence of multicollinearity in the study's data set, I examined three indicators: (1) a correlation matrix including all independent variables, (2) the tolerance statistic, and (3) the variance inflation factor (VIF).

First, I calculated zero-order Pearson correlation estimates among the independent/predictor variables (Table 3.5). All correlations were below the values of .80 and .90 that scholars claim are grounds for collinearity concern (Grewal, Cote, & Baumgartner, 2004; Kaplan, 1994; Kennedy, 1992). Then, I checked for multicollinearity by calculating six squared multiple correlations (R^2_{smc}), with each variable being the

criterion and the other variables being predictors. The R^2_{smc} were also below .90, thereby indicating that there is not a problem with multicollinearity (Kline, 2011).

Second, I examined the tolerance statistic—the procedure of assessing the independence of each variable from other variables (Darlington, 1990). A data set is free of multicollinearity concerns when the tolerance estimate is greater than .20. In my analysis, all independent variables of this study achieved a tolerance score above the minimum threshold. Lastly, I analyzed the VIF score, which assesses the extent to which the variance of a regression coefficient is inflated due to multicollinearity (Hair, Anderson, Tatham, & Black, 1995). The VIFs for each independent variable did not exceed four, thereby indicating there was not a problem with multicollinearity (Keith, 2006; Miles & Shevlin, 2001).

Table 3.5

Summary of Bivariate Correlations of Variables in Primary Study

Variable	1	2	3	4
1. Online Health Community Participation	1			
2. Identification with the Community	.43**	1		
3. Interpersonal Bonds with Community Members	.17*	.23*	1	
4. Perceived Social Support	.29*	.26**	.21*	1

Note: N = 356. * $p \leq .05$ ** $p \leq .01$ *** $p \leq .001$

Operationalization of Variables

After the consent form (Appendix A), survey instructions directed participants to (a) think about the online health community that they used the most frequently, and (b)

respond to items in the survey based on their user experiences. Participants then completed four measures and demographic questions: OHC participation, identification with the community, interpersonal bonds with other community members, and perceived social support. Finally, participants completed demographic questions at the end of the survey. The following section describes the measurement of each of these variables (see Appendix C for a complete copy of the instrument).

Independent/Predictor Variable

OHC participation. To assess OHC users' participation in OHCs, I drew from the social networking site (SNS) participation scale developed by Brandtzaeg (2012). In 2011, Brandtzaeg and Heim first created an 18-item participation scale to (a) identify and predict SNS use and (b) better understand participation inequality in SNSs. Brandtzaeg (2012) extended the scale to include 14 more items to account for the informational and recreational purpose of SNS use, which yielded a 32-item measurement of SNS participation. Although the scale was not intended for online health communities, I found 20 items from the original scale were suitable for measuring the level of participation (i.e., lurking vs. posting) and the mode of participation (i.e., task mode and/or relational mode) simultaneously: "write contributions", "update status", "add arrangements", "fix user profile", "upload photos", "watch photos", "find useful information", "find information about friends", "see if somebody has contacted me", "get in touch with new people", "read new contributions", "arrange appointments", "educational purposes", "write/chat with close friends", "write/chat with acquaintances", "write/chat with unknown", "discussion/debate", "follow discussion threads", "run group(s)", and

“profile surfing”. In this study, I used the following prompt for the scale: “Think specifically about your participation in the online health community and answer the following questions.” Example items from this scale included, “I read other people’s posts on the site” and “I write/chat with close friends”. Each item was answered using a 7-point Likert scale ranging from *never* (=1) to *every time* (=7).

To further reflect users’ participatory behaviors within OHCs, I added eight items based on the observational data collected in the pilot study: “post questions”, “check announcements”, “give suggestions”, “welcome new members”, “encourage people”, “express empathy”, “send private messages”, and “connect people with others”. To validate the 28-item scale, I conducted principal component analysis and confirmatory factor analysis. Four items were dropped because of low factor loadings: “add arrangements”, “educational purpose”, “see if somebody has contacted me”, and “watch photos” (detailed results are reported in Chapter 4). The final 24-item scale had $M = 4.1$, $SD = .92$, and Cronbach’s $\alpha = .79$.

Mediator Variables

Identification with the community. Adapted from Mael and Ashforth’s (1992) organizational identification scale, a five-item measure was used to assess identification with one’s OHC. This measure has been broadly used in prior identification research (e.g., Dailey & Zhu, 2016; Kreiner & Ashforth, 2004). An example item reads, “When someone criticizes my community, it feels like a personal insult.” The response options ranged from *strongly disagree* (= 1) to *strongly agree* (= 7). In this study, the $M = 4.8$, $SD = .95$, and the Cronbach’s $\alpha = .90$.

Interpersonal bonds with other community members. To assess one's interpersonal bonds with other OHC members, I used a three-item measure adapted from Prentice et al. (1994). An example item reads, "How close do you feel close to the other members of your OHC?" Participants responded to each item by circling a number on a 7-point scale; higher numbers correspond to more positive responses. Each participant's responses to the three items was averaged to form a single index of interpersonal bonds. In this study, the three-item scale had $M = 3.2$, $SD = 0.81$, and the Cronbach's $\alpha = .81$.

Outcome Variable

Perceived social support. Perceived social support was measured with the Social Provisions Scale (Cutrona & Russell, 1987; 1990). The 29-item scale measures five dimensions of social support (i.e., informational, emotional, esteem support, network, and tangible). In addition, the Social Provision Scale also measures a dimension labeled nurturance, which is the general perception that "others rely upon oneself for their wellbeing" (Cutrona & Russell, 1987, p. 38). While nurturance is not a standard measure of social support, it was retained in the current survey to assess how important the opportunity to help others might be to participants. An example item reads, "There is a trustworthy person I could turn to in this community for advice if I were having problems." Participants rated each item on a 7-point Likert-type scale, ranging from *strongly disagree* (= 1) to *strongly agree* (= 7). Items were summed with some items reverse scored. Higher scores indicated higher perceived social support. In this study, the 29-item scale had $M = 4.1$, $SD = 1.01$, $N = 356$, and the Cronbach's $\alpha = .80$.

Control Variables

At the beginning of the questionnaire, I collected basic OHC usage information, including length of account ownership, community size, number of friends connected through the community, and number of community member that they have met in person. In addition, I collected demographic information asking participants to report their age, race/ethnicity, highest level of education obtained, annual household income, and health condition. Given the influence of demographic characteristics such as age and education on information seeking and sharing (Han et al., 2014), it is logical to assume that certain demographic characteristics (e.g., health condition and length of account membership) may have extraneous influence on the relationship between OHC participation and perceived social support.

Data Analytic Plan

In *Study One*, RQ1 asks if OHC users' participation can be classified into meaningful patterns. To answer this question, I used cluster analysis to develop the typology of OHC participation. In *Study Two*, there is an overarching hypothesis: OHC participation will explain perceived social support through identification with the community and interpersonal bonds with other community members. I used structural equation modeling (SEM) to examine the proposed mediation model. The following section describes research procedure for each data analytic procedure.

Overview of Cluster Analysis Procedure

Cluster analysis is a multivariate statistical procedure that identifies homogeneous groupings within a sample using variables specified by the researcher (SPSS, 1997;

Aldenderfer and Blashfield, 1984). It seeks to minimize within-group variance and maximize between-group variance (Borden, 2005; Everitt, Landau, Leese & Stahl, 2011). In other words, cluster analysis classifies similar cases across a series of dimensions into different relatively homogenous clusters (subsets). This method of categorizing objects into naturally occurring groups are suitable for this study, because it helps partitioning of a data set into subsets of participation patterns.

When conducting a cluster analysis, Hair and colleagues (2008) have proposed a six-stage model, which was utilized in this study to guide the cluster analysis process. The six-stage process is outlined in Table 3.7. In the following section, I discuss each stage and review its specific application in this study.

Table 3.6
Six Stages of Cluster Analysis

Stage	Purpose
One	Determine Objectives
Two	Select Research Design
Three	Meet Assumptions
Four	Derive Clusters and Assess Fit
Five	Interpret the Clusters
Six	Validate and Profile Clusters

Note. This table was adapted from Hair et al. (2008)

Determine objectives. The first stage was to determine the objective of the cluster analysis. The goal of this research was to develop a typology of online health community users. The development of this typology was based on theoretical foundations derived from previous literature (see more details in Chapter Two).

Select research design. This step involved five critical aspects of typology development: sample size, outliers, measurement, similarity, and standardization. First,

sufficient sample size is important as it ensures that the structure of cluster formation is represented appropriately (Hair et al., 2008). There was no rule regarding the minimum number of sample size for cluster analysis. I included an extended review of related literature in the section called “sample size and power calculation”. Second, important to examine in this stage were outliers. I evaluated the sample for outliers in several ways, including a univariate approach of standardizing the variables, a bivariate examination of the plotted variables, and the calculation of the Mahalanobis Distance between the two variables. Results of outlier examine are discussed in the “Data Screening” section of this dissertation.

The third aspect of research design considered at this stage of the process was the decision of how to measure similarity. Three main methods of determining similarity were widely used in previous studies: correlation measures, association measures, and distance measures. Correlation measures were inappropriate for cluster analysis as they measure the pattern of the relationship between the variables rather than the magnitude of the relationship. Association measures were not suitable for this analysis either, because they are used with nonmetric variables while all of the variables included in the cluster analysis were metric. Distance measures determine the proximity of observations to another across all variables included in the analysis. When measurements of distance are computed, the inverse of this distance measure can then be viewed as a measurement of similarity. For the cluster analysis, two distance measures were utilized: Euclidean distance and Squared Euclidean distance. Euclidean distance is the most recognized measure of distance (Rapkin & Luke, 1993). Squared Euclidean distance was chosen for

its usefulness with correlated variables (as reading posts and finding new information are).

Another critical step of research design was the selection of variables, which served as indicators of similar patterns in a sample. Guided by theories and/or previous research, researchers should select variables that are directly useful in the characterization of clusters (Rapkin & Luke, 1993). The items used in the cluster analysis were adapted from existing studies (Brandtzæg & Heim, 2011; Brandtzæg, 2012). The measures covered two theoretically driven areas—task-oriented participation and relational-oriented participation. Ideally, the number of variables in each of these areas would be nearly identical (Hair, et al., 1998). There were 13 measures for task-mode and 13 measures for relational mode.

Finally, the issue of standardization of variables is addressed in this stage. The goal of standardization is to minimize the differences between scales that may unduly influence the generation of clusters. In this research, variables were standardized using the most common standardization technique of z-scores.

Meet assumptions. As suggested by Hair et al., (2008), cluster analysis should meet assumptions inherent in the procedure, including issues of normality, linearity, homoscedasticity, and multicollinearity. I have provided a detailed discussion of those issues in the “Data Screening” section of this dissertation.

Derive clusters and assess fit. This stage involved the selection of clustering algorithms to partition the variables into appropriate number of clusters (Hair et al., 2008). SPSS 24 provides three different procedures for cluster analysis: hierarchical

cluster analysis, k-means cluster analysis, and two-step cluster analysis involving both hierarchical cluster and k-means cluster. Following the recommendation of DiStefano & Mindrila (2012), I used a two-step cluster analysis strategy to determine the number of clusters. This analytic plan was chosen because it enhances the likelihood of establishing meaningful clusters that reliably reflect the underlying data structure (Borgen & Barnett, 1987; Garson, 2012; Mooi & Sarstedt, 2011).

To gain a rough estimate of a cluster solution, I first performed a hierarchical clustering analysis (Ward, 1963). As Aldenderfer and Blashfield (1984) argued, hierarchical clustering analysis is the most popular clustering method in social science, because it creates groups with minimum variance within a cluster. Using this strategy, each case represents its own cluster initially. Cases that are most similar (i.e., those with the smallest between-subject distance) are merged to form higher order clusters. This process stops when all cases are grouped into a single cluster. While there is no one established method for determining when the most representative number of clusters has been created, I measured the percent change in heterogeneity between the agglomeration coefficients for each cluster solution. According to Hair and colleagues (2008), this method has the advantage of being “the simplest and most widespread rule” (p. 594). Potential cluster solutions are selected when there is a marked increase in the agglomeration coefficient than is found with other numbers of cluster solutions. Increases in the agglomeration coefficient indicate a loss of homogeneity within the cluster groups.

However, the disadvantage of hierarchical clustering analysis is that once a case is assigned as a member of a particular cluster, it is irrevocable. In other words, when two

clusters have been joined together, they cannot be separated as the clustering procedure continues. To overcome this drawback, I used a K-means procedure to refine the hierarchical cluster solution. The K-means procedure allows for cases to move among clusters to find the best fit (MacQueen, 1967). Unlike hierarchical techniques where cases remain in the initial cluster, K-means cluster analysis assign cases to clusters based on an iterative process of modifying k randomly generated cluster centers until the change in centers is minimal. This technique serves as an additional for validating the solution with k clusters identified in the hierarchical analysis (Garson, 2012), thus gaining the benefits of both clustering algorithms (DiStefano & Mindrila, 2012).

Interpreting and profiling the clusters. The last two steps involved the interpretation of results. A common method for interpretation is through analysis of the cluster centroids generated during stage four. Clusters should have meaning that can be interpreted and which provide practical guidance (Rapkin & Luke, 1993). To interpret and profile clusters, I conducted a series of analyses of variance (ANOVA). The use of ANOVAs would (1) reveal how the clusters are unique from each other and (2) describe differences for each major variable (i.e., identification with the community, interpersonal bonds with other members, and perceived social support) among the clusters.

Overview of SEM Procedure

To test the hypotheses and the validity of the full model proposed in *Study Two*, I conducted structural equation modeling (SEM) analysis using Mplus 7.0 (Muthén & Muthén, 2010). SEM tests hypothesize linear relationships and obtains estimates of the relationships among both observed and latent variables (MacCallum & Austin, 2000).

SEM is superior to a conventional regression approach because it allows for the simultaneous modeling of several related regression relationships, whereas the conventional regression approach allows the modeling of only one regression equation at a time and one dependent variable at a time (Muthén & Muthén, 2007).

SEM analysis consists of a two-step modeling procedure (Anderson & Gerbing, 1988). In the first step, the measurement model is tested to determine how well the indicators represent the constructs (i.e., the latent variables). If necessary, changes are made to improve the fit of the measurement model, so long as the changes are consistent with theory (Kline, 2005). In the second step, the structural model (i.e., the mediation model in my study) is analyzed to test the hypothesized relationships among variables. I conducted the two-step modeling analysis following Kline's (2011) guidelines, which include (1) model specification, (2) model identification, (3) model estimation, (4) model evaluation, and (5) model modification and re-specification. In the following subsections, I describe how the data were analyzed through these procedural steps.

Model specification. In the first step, structural equation modeling requires researchers to draw a model diagram that corresponds to the pattern of directional and non-directional relationships amongst the variables of interest (MacCallum, 1995). To do so, the researchers should use theory and previous research to indicate which variables to include in the model and determine every relationship and parameter. Therefore, based on the comprehensive literature review conducted in Chapter Two, I created the theoretical mediation model detailed in Figure 3.1.

Mediating effects specify how a given effect occurs (Holmbeck, 1997). It is generally hypothesized that the independent variable causes the mediator, and the mediator causes the outcome (Holmbeck, 1997). The proposed model examines the mediating relationships between the independent variable (i.e., OHC participation), the mediators (i.e., identification with the community, interpersonal bonds with other members), and the dependent variable (i.e., perceived social support). Once the theoretical model was specified, the next step was to determine whether the model was identified.

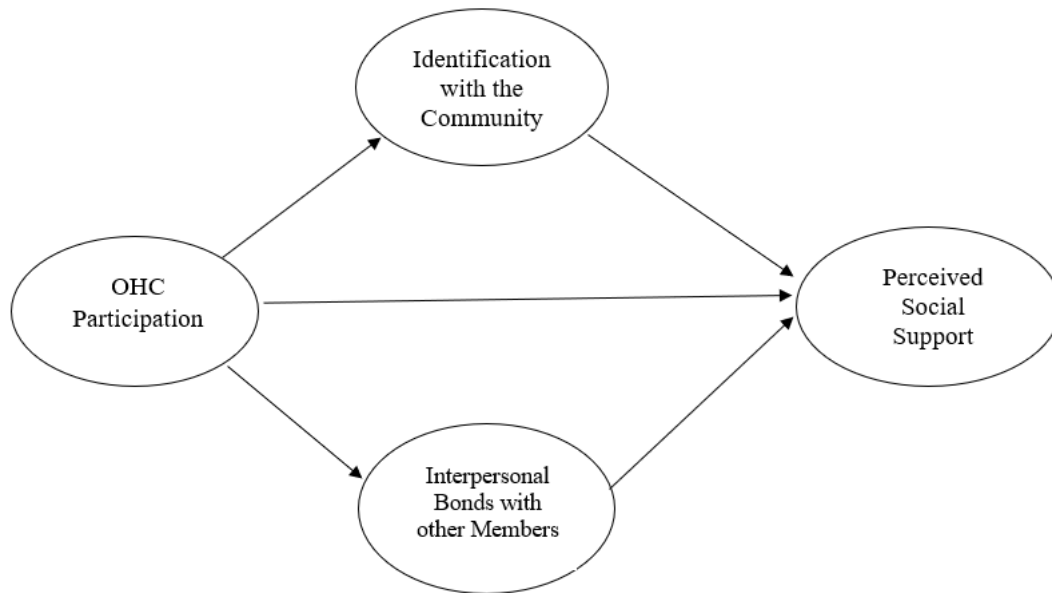


Figure 3.1. *Mediation Effects of the Hypothesized Model*

Model identification. Identification refers to whether it is theoretically possible to derive a unique set of estimates for all unknown parameters in the model. One basic principle of model identification is that the number of unique pieces of information provided by the data cannot exceed the number of estimated parameters (i.e., unknown parameters). The knowns consist chiefly of the variances and covariances of the

measured variables (but may include other elements as well), while the unknowns consist of model parameters. Model identification is an important concern for SEM researchers because the methodology gives users the freedom to specify models that are “over-identified”, “just-identified”, and “under-identified” (Garson, 2015; Kline, 2010). Having more known parameters than un-known parameters results in an over-identified model; conversely, having more un-known parameters than known parameters leads to an “under-identified” model. A statistical model is "just-identified" if the known parameters available are equal to un-known parameters. A general rule of thumb regarding model identification is that a researcher can proceed with the his/her analysis if the model is “over-identified”.

I applied the t-rule (Blunch, 2008) to determine whether a model is “over-identified”. The t-rule uses the following equation to achieve the number of observed parameters: $p(p+1)/2$, where p equals the number of observed variables. In my particular data set and model, I calculated 36 observed parameters and 30 estimated, or free, parameters. Therefore, I concluded that my model was over-identified, which was a signal that I could move forward with my data analysis.

Model estimation. Following model specification and identification, the third step was model estimation. The primary goal of this step is to determine the goodness-of-fit between the specified model and the observed data. The estimation process involves the use of particular fitting functions that minimize the difference between the observed and the model-implied matrices. A few model estimation methods are available to estimate the model parameters including maximum likelihood (ML) estimation (Bollen,

1989; Kline, 2010), bootstrap resampling method (Nevitt & Hancock, 2011), generalized least squares (GLS), three-staged least squares (3SLS; Zellner & Theil, 1962), and partial least squares (Gefen, Straub, & Boudrea, 2000). I chose maximum likelihood estimation for this study because of two reasons: First, it is the default method in most SEM computer tools, including Mplus, and the most commonly used method for analysis with continuous outcomes; second, ML has been found to provide more realistic fit indices and less-biased parameter estimates (Olsson, Foss, Troye, & Howell, 2000).

Model evaluation. Once the process of model estimation has taken place, the evaluation step begins. The analytical task of this step is to determine how well the data corresponds to the model and whether the model needs to be readjusted. According to the recommendation of Hu and Bentler (1995), I used several model fit indices to evaluate the model. Table 3.6 describes each of the indices along with their corresponding statistical criteria. The chi-square test of model fit (χ^2) is the most common test of exact fit (Weston & Gore, 2006). In SEM, it is desirable to have a non-significant χ^2 , which suggests that the model is a good fit for the data. However, χ^2 test statistic is sensitive to Type II error when the sample size is large—that is, above 200 cases (Garson, 2015). Since this study had a sample size that was comparatively large ($n = 356$), it was likely to achieve a statistically significant χ^2 value. Additionally, the χ^2 can also be significant when variables in the specified model are correlated. Given the results of my pilot study, the likelihood of having a significant χ^2 was greater than if the variables in my model were significantly correlated with one another. This might potentially lead to a false negative or Type I error (Kenny, 2014).

Table 3.7.

Fit Indices and Statistical Criteria

Fit Index	Criterion for Indicating Good Fit
Chi-square (χ^2) test	If the test statistic is non-significant ($p > .05$) this indicates a good model fit. However, this test is not reliable for sample sizes over 200.
Goodness of Fit Index (GFI)	Values $> .90$ indicate good fit
Comparative Fit Index (CFI)	Reasonable fit = values $> .93$ Perfect fit = 1.0
Root Mean Square Error of Approximation (RMSEA)	Good fit $\leq .05$; Adequate fit $\leq .09$; Poor fit $\geq .10$
Standard Root Mean Residual (SRMR)	Good fit $\leq .05$
Chi-square/degrees of freedom (χ^2/df) ratio	Values smaller than 3

Given the limitations of chi-square test as the only criteria for model fit, I used additional fit indices that were widely used by the SEM community (Bentler, 1990; Browne & Cudeck, 1993; Garson, 2015; Hu & Bentler, 1995). For example, the Comparative Fit Index (CFI; Bentler, 1990), with values ranging from .0 to 1.0 and with values above .90 indicating acceptable fit, (Hu & Bentler, 1995). The Root Mean Square Error of Approximation (RMSEA; Steiger, 1990) is another fit index with values of less than .10 and with a maximum upper bound of 90% CI of .10 indicating acceptable fit (Brown & Cudek, 1993). Also, the Standardized Root Mean Square Residual (SRMR; Kline, 2005) is yet another fit index, with values less than .10 indicating acceptable fit

(Bentler, 1995). Lastly, I assessed the model fit using the R^2 value to determine how much variance is accounted for in each observed model variable (Bollen, 1989; Raykov & Widaman, 1995). The R^2 value must be at least 0.2 and ideally above 0.3 to be meaningful and worthy of reporting (Chin, 1998). If the model fits data well and results are interpretable, the SEM analysis can stop after this step.

Model modification and re-specification. Lastly, if the model does not fit the data, model modification and/or re-specification are often used to increase model fit. In this instance, the researcher makes a decision regarding how to delete, add, or modify parameters in the model. This process involves two general approaches known in the SEM literature as model building (i.e., adding plausible paths to a model or releasing model constraints) and model trimming (i.e., eliminating one or more nonsignificant paths in a model to force model constraints). However, researchers must ensure the process of modifying and/or re-specifying a model is always theoretically meaningful. For the specified model of this study, the goal was confirmatory regarding the mediation effect rather than exploratory; thus, I was very cautious when making any changes to the model.

Sample Size and Power Calculation

Determination of appropriate sample size is a critical issue in SEM. Without the participation of adequate sample, some statistical estimates in SEM, such as standard errors and parameter estimates, may not be accurate (Kline, 2011). For normally distributed data, an N greater than 200 is considered large for most SEM estimation

models (Kline, 2005); thus, this study has a sufficient sample size ($N = 356$) to conduct a SEM procedure.

For cluster analysis, there is no generally accepted standard regarding minimum sample sizes (Dolnicar, 2002; Dolnicar, Grun, Leisch, & Schmidt, 2013). According to Kumar and colleagues (2017), hierarchical clustering should be used when the data set is small. K-means clustering is widely used for moderately sized data set, especially for studies that have predetermined number of clusters. The two-step procedure is recommended if a researcher has a large data file (1,000 cases is large enough for clustering) or a mixture of continuous and categorical variables (citation). However, there are no fixed cut-off points for assessing sample size (small, moderate, and large).

Only two recommendations about the appropriate ratio of cases (sample size) to numbers of variables had been published at the time of this research. First, Formann (1984) recommended a sample size of at least 2^m (preferably $5 \cdot 2^m$), where m equals the number of clustering variables. This recommendation is problematic because it is specifically provided in the context of chi-square test for latent class analysis grouping binary data. Second, Qui and Joe (2009) suggested that the sample size should be larger than 10 times the number of variables includes in the cluster analysis times the number of clusters ($10 \cdot d \cdot k$, with d representing the number of variables included in the cluster analysis and k representing the number of clusters). However, this recommendation was not supported by any explanation or justification, which might lead to grossly over- or underestimated sample size requirement. Due to the lack of rules, I conducted cluster

analysis using 356 available responses collected for the primary study, while critically monitoring if the dimensionality was too high for the number of cases to be grouped.

Chapter Summary

In this chapter, I detailed the method for carrying out the proposed study. In particular, I described the pilot and primary study research site, data collection procedure, and data analytic plan. Additionally, I reviewed the measurements of each variable included in this study. The subsequent chapter offers a complete review of the data analysis process as well as the results from model testing.

CHAPTER 4: FINDINGS

Factor Analyses and Descriptive Statistics

Before running the primary structural equation modeling (SEM) for the mediation model, I conducted factor analyses for each variable measured in this study. Following the recommendations of Teddlie and Tashakkori (2009) and Gaskin (2013), this procedure combined principal component analysis (PCA) and confirmatory factor analysis (CFA). The objective of these analyses was to determine the amount of shared variance that existed amongst a set of variables, thus ensuring that the scales used in the study all measure one factor (Williams, 1992). With that said, I first conducted PCA with a varimax rotation using SPSS 24 to assess scales for OHC participation, identification, interpersonal bonds, and perceived social support. I applied three criteria to determine the number of components in each scale: (1) factor loadings, (2) Kaiser's rule (i.e., any eigenvalues greater than one indicates internal reliability; Kaiser, 1960), and (3) screen plots (i.e., visual representation of where the 'leveling off' of eigenvalues occurs). I then used CFA on all of the aforementioned measures.

For the OHC participation scale, the PCA results suggest that the 28-items did not result in a cleanly loaded factor. Specifically, the loadings of four items were below the .70 threshold: "I add arrangements on the site," "I use the site for educational purpose," "I check the site to see if somebody has contacted me," and "I watch photos." Table 4.1 presents all the factor loadings of all 28 items, the eigenvalue, and variance accounted for regarding the scale. To improve the fit of this construct, I removed the above four items with poor factor loadings. The remaining 24 items loaded on a single factor and accounted for 81% of the total variance and the resulting Cronbach alpha yielded a .82 — whereas the previous 28-item scale yielded a Cronbach's alpha of .79. A plausible explanation is that the variation of different community features might lead to

participants' inconsistent responses, such as private messaging function and multimedia support (Ren et al., 2012). For example, within Facebook communities, users could share images files with the whole community and/or individuals who had joined the group. For mobile-only communities such as Stupid Cancer, users could only send pure texts.

Table 4.1

Factor Analysis of the OHC Participation Scale

Items	Loadings
I surf other people's profiles on the site.	.95
I get contacted by other people on the site.	.93
I read other people's post in on the site.	.90
I post questions on the site.	.89
I answer questions on the site.	.87
I look for a new friend on the site.	.85
I welcome new people on the site	.85
I check announcement on the site.	.82
I send private messages to others on the site.	.81
I get in touch with new people on the site.	.80
I update my profile status on the site.	.80
I post/share pictures on the site.	.78
I express my empathy to people's posts on the site.	.78
I ask for suggestions on the site.	.77
I post/share videos on the site.	.76
I run community groups on the site.	.75
I give suggestions to people on the site.	.75
I write/chat with strangers on the site.	.73
I seek for new information on the site.	.73
I encourage people on the site.	.73
I write/chat with acquaintances on the site.	.72
I follow discussion threads on the site.	.71
I engage in discussions on the site.	.71
I connect people with others on the site.	.70
I check if somebody has tried to contact me on the site.	.50
I arrange appointments with other people on the site.	.31
I watch photos on the site.	.24
I use the site for educational purpose.	.14
Factor Eigenvalues	15.42
% of Variance	32.81

Note: Factor loadings over .70 appear in bold. Four items that had poor loadings were removed from the analysis

For the identification scale, all five items loaded onto a single component that accounted for 80% of the total variance. The factor loading for each item was .85 or greater. The Cronbach's alpha measure yielded a .90. For the interpersonal bonds scale, all three items loaded onto a single component that accounted for 64% of the total variance. The factor loading for each item was .80 or greater. The Cronbach's alpha measure yielded a .81. For the perceived social support scale, all 29 items loaded onto a single component that accounted for 87% of the total variance. The factor loading for each item was .77 or greater. The Cronbach's alpha measure yielded a .80. Following factor analyses, I examined the correlations among all variables in this study. As shown in the Table 3.5, all of the variables in this study were significantly correlated with one another at either the .01 or .05 level.

Primary Data Analysis: Typology Development (Study One)

Before conducting cluster analysis, I revisited outliers that were removed during the initial data screening. The reason was that cluster analysis is very sensitive to outliers, thereby removing "apparent" outliers might result in losing valuable insight. For this reason, compelling evidence was needed before an outlier was omitted from the data. By revisiting the nine removed cases, I decided to omit them from the cluster analysis, because these cases had extreme values that exceeded 10 standard deviations using z scores.

RQ1 asked if meaningful user types could be identified to reflect different participation levels of participation modes. As noted in the data analytic plan (Chapter 3), I used a two-step approach to identify solutions for OHC users' participation patterns, which included hierarchical cluster analysis and K-means cluster analysis.

First, hierarchical cluster analysis began with all cases individually. In the initial iteration, two cases “closest” to each other were joined to form a cluster. Then, in the following iteration, two more cases were combined, or a third case was joined to the previously created cluster. This iteration process continued until all cases were in one cluster. The number of iterations is $N-1$; thus, in this study, the number of iterations is $356-1$, or 355. As suggested by Hair et al. (1998), I used the squared Euclidean distance to measure the distance between cases. Because Euclidean distance measurement is sensitive to the variables’ units of measurement, the variables were standardized to the z score to avoid the possible bias effects of differences in variance across variables. The coefficients statistic was used as the criterion for deciding how many clusters best fit the data.

I computed and compared multiple cluster solutions (ranging from two to five clusters). A large increase in the coefficient occurred at stage 353. The five-cluster solution in this analysis had a coefficient value of 156.177 followed by a value of 172.532 for a four-cluster solution, which accounted for 29.76% of change in coefficient. This change is seven times greater than the solution changes from ten to nine, nine to eight...five to four. This large increase in the coefficient results indicated two relatively heterogeneous, or distant, clusters were combined. The solution preceding this large increase could provide a stopping point for cluster formation. This would result in the formation of a four-cluster solution. The increase in the coefficient from stage 354 to 355 was small which would suggest the four-cluster solution is preferable. Table 4.1 presents partial agglomeration schedule for cluster analysis.

To minimize biases inherent in specific cluster analytical methods, a series of k-means cluster analyses were conducted to further assess the appropriateness of these solutions. Cluster numbers were set at 4, 5, and 6. The three clusters were internally validated by re-running the

cluster solutions in randomly divided split half data sets. Comparison of the four-cluster solution revealed all four clusters to be validated on at least 3 out of 5 split half comparisons. Only two of the clusters for the five-cluster solution were validated on 4 of 5 split half comparisons. Clusters six produced even fewer validated clusters based on split half comparisons. This indicated that the four-cluster solution was robust.

Upon the final selection of the four-cluster solution, I developed descriptive terms of the cluster groups. First, Cluster 1 was described as hybrid mode posting. This cluster described posters who were in both high task mode and high relational mode. As shown in Table 4.4, their OHC participation focused on information seeking and providing (e.g., answering questions and offering suggestions) as well as relationship building with other users (e.g., looking for new friends and encouraging others). Second, Cluster 2 was categorized as task-mode posting. Users in this mode were likely to pay more attention to the transmission of information, suggestions, or guidance. For example, they frequently read others' posts ($M = 4.9$), found useful information ($M = 5.9$), and followed discussion topics ($M = 5.8$). Third, Cluster 3 was described as relational-mode posting. Users in this mode tended to engage in one-on-one private messaging with friends in the community ($M = 6.5$), express empathy regarding similar others' situation ($M = 6.0$), and welcome new members to the community ($M = 5.2$). Lastly, Cluster 4 was described as task-mode lurking. Users in this mode were only interested in seeking information that meet their needs, such as finding useful information ($M = 5.9$) and following discussion topics ($M = 5.1$).

To further interpret the four-cluster solution of user types, I conducted a series of one-way ANOVA tests. The analytical goal of those tests was to determine whether significant difference existed among identified cluster groups for the three major factors (i.e., identification with the community, interpersonal bonds with other community members, and perceived social

support). If significant difference did exist, I utilized Tukey HSD post-hoc tests to determine how the groups were differentiated from each other concerning the identified factors. Only significant differences were reported in the following paragraph.

Table 4.2
Partial Agglomeration Schedule for Cluster Analysis

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage	Change in Coefficient	Percent Difference	Number of Clusters
	Cluster 1	Cluster 2		Cluster 1	Cluster 2				
350	13	83	150.321	319	322	532	4.717	5.63%	7
351	1	22	154.038	321	328	353	2.129	8.41%	6
352	3	22	156.177	328	331	354	16.435	3.99%	5
353	4	13	172.532	332	338	355	1.464	29.76%	4
354	1	3	173.996	345	346	356	1.858	19.53%	3
355	2	4	174.526	348	353	356	0.67	12.50%	2
356	1	2	175.922	354	356	0	1.406	21.12%	1

Table 4.3
Results of ANOVAs and Tukey HSD Post-Hoc Tests

Variable	Cluster 1 (n = 74)	Cluster 2 (n = 105)	Cluster 3 (n = 61)	Cluster 4 (n = 116)	F-test Statistic	Multiple Comparison
Identification	4.21	4.54	3.96	2.02	3.62*	1>4* 2>4* 3>4*
Interpersonal Bonds	3.73	3.09	4.19	1.97	5.93**	1>2* 1>4** 2>3* 2>4**
Perceived Social Support	4.32	3.98	4.10	2.15	7.92*	1>4** 3>4*

Note. N = 356. * $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Identification with the community was found to differentiate between clusters, $F(2, 61) = 3.62, p < .05$. A post hoc Tukey test showed that Cluster 1, Cluster 2, and Cluster 3 had greater levels of identification with the community than Cluster 4, all at the significance level of $p < .05$. There was also a statistically significant difference between the interpersonal bonds with other community members, $F(2, 59) = 5.93, p < .001$. Cluster 1 had a greater level of interpersonal bonds with other community members than cluster 2 ($p < .05$) and cluster 4 ($p < .001$). Cluster 3 had a greater level of interpersonal bonds with other community members than Cluster 2 ($p < .001$) and Cluster 4 ($p < .05$). The effect of user types on perceived social support was also significant, $F(2, 44) = 7.92, p < .05$. Both Cluster 1 ($p < .001$) and Cluster 3 ($p < .05$) had greater levels of perceived social support than Cluster 4. Table 4.3 presents results of ANOVAs and Tukey HSD post-hoc tests. Table 4.4 includes mean scores within each cluster.

Table 4.4

Mean Scores within Each Cluster

Items	C1 Hybrid Mode Posting	C2 High-Task Mode Posting	C3 High-Relational Mode Posting	C4 High-Task Mode Lurking
Read post	4.5	4.9	4.2	5.3
Post questions	3.3	3.6	1.1	2.1
Answer questions	5.1	4.4	4.6	2.3
Check announcement	2.9	3.1	2.0	4.9
Post/share pictures	4.6	3.9	1.2	1.6
Post/share videos	4.2	3.2	1.4	1.6
Engage in discussions	4.9	4.6	4.2	1.7
Update status	3.6	5.1	3.5	2.9
Give suggestions	4.8	2.9	3.6	3.1
Find useful information	5.6	5.9	3.9	5.9
Follow discussion topics	4.1	5.8	4.0	5.1
Fix user profile	4.2	3.2	4.0	2.8
Check others' profiles	4.6	3.0	4.9	4.2
Look for new friends	4.9	2.8	5.2	2.8
Welcome new members	4.1	2.5	5.2	2.6
Write/chat with friends	3.4	2.1	4.4	1.4
Find information about friends	4.7	2.6	5.4	2.1
Write/chat with acquaintances	4.1	3.8	5.0	2.2
Write/chat with strangers	4.0	3.9	5.0	1.9
Encourage people	5.2	4.6	5.2	2.2
Express empathy	5.6	5.1	6.0	2.8
Send private messages	4.2	2.4	6.5	1.1
Run community groups	2.4	1.2	5.0	1.8
Connect people with others	4.1	1.6	5.2	1.9

Primary Data Analysis: Testing the Mediation Model (Study Two)

As noted in my data analytic plan, I analyzed the proposed mediation model by conducting a two-step structural equation modeling (SEM) analysis. I first assessed how well the indicators represent the constructs by testing the fit of the measurement model using confirmatory factor analysis. The initial measurement model with unit-loading indicators to scale latent constructs indicated a good model fit: $\chi^2(26) = 102.64, p = .03, CFI = .95, TLI = .97,$

RMSEA = .01, and SRMR = .02. Neither of the cross-loadings of one measurement item over multiple constructs nor low-factor loadings were found to compromise the overall model fit.

After achieving adequate fit for the measurement model, I used SEM to test the two mediation paths (H3 and H6). The results revealed that the structural model was a good fit to the data: $\chi^2(7) = 435.06, p = .17, CFI = .94, TLI = .98, RMSEA = .04,$ and $SRMR = .05$. The complete model, shown in Figure 1, shows support for H1. There was a significant indirect effect of OHC participation on perceived social support through identification with the community ($b^* = 0.227, BCa\ CI: .075, .221, p < .001$), and interpersonal bonds with other community members ($b^* = 0.112, BCa\ CI: .037, .159, p < .01$). Therefore, H3 and H6 are supported. Figure 4.1 shows the mediation model with completed coefficients, and Table 4.5 presents the standardized and unstandardized regression weights of the mediation model.

To further compare the two mediating effects, I followed the recommendation of Lau and Cheung (2010) to compare the bias-corrected (BC) bootstrap interval for testing the difference between two standardized mediation effects. Specifically, I used the NEW parameter option in Mplus—which was defined as $D_M (D_M = M1 - M2)$ —to test the significance of the difference between the two specific mediation effects, where M1 was the first mediation effect (identification) and M2 was the second mediation effect (interpersonal bonds). The BC confidence interval for D_M is between .38 and .72, which did not contain zero. Such finding suggested that M1 was significantly larger than M2. Furthermore, as suggested by Preacher and Hayes (2008), I also conducted a χ^2 difference (Wald) test by imposing equivalent constraints on the structural paths. The corresponding $\Delta \chi^2$ value with $df = 1$ for comparisons represented by D_M was 2.12 ($p < .01$), which demonstrated the same conclusion as the BC bootstrap confidence interval method. I therefore conclude that the mediating effect through identification with the

community was significantly larger than the mediating effect through interpersonal bonds with other members.

In the model, OHC participation was significantly associated with identification with the community (H1; standardized estimate = .33, $p < .01$) and interpersonal bonds with other members (H4; standardized estimate = .18, $p = .037$). Identification with the community was significantly associated with perceived social support (H2; standardized estimate = .26, $p < .01$). Interpersonal bonds with other members was significantly associated with perceived social support (H5; standardized estimate = .12, $p = .042$).

The R^2 values of the latent dependent variables indicated that OHC participation accounted for 41% of variance in identification with the community, 29% of variance in interpersonal bonds with other community members, and 3.7% of variance in perceived social support. For the outcome variable perceived social support, 45% of the variance was explained by the combination of OHC participation, identification with the community, and interpersonal bonds with other community members.

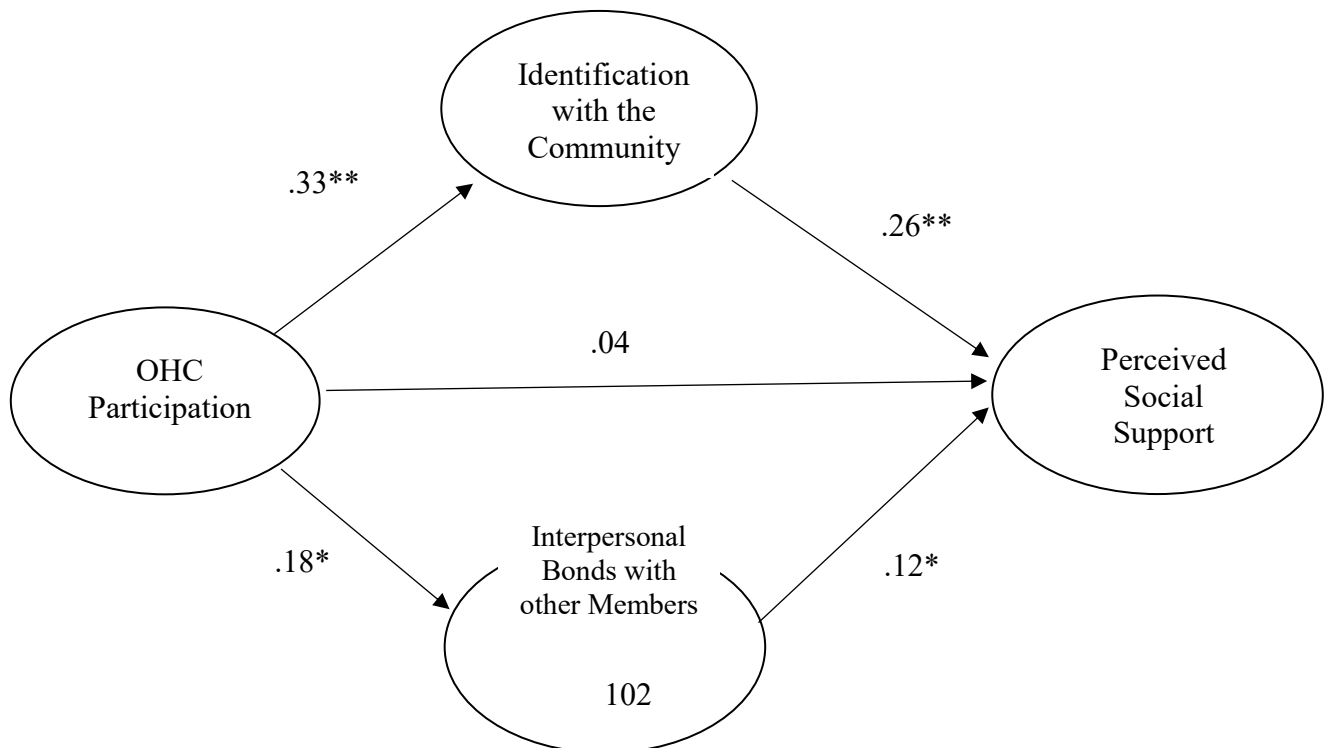


Figure 4.1. *Standardized Path Estimate Results of the Mediation Model*

Note: N = 356. * $p \leq .05$ ** $p \leq .01$ *** $p \leq .001$

Table 4.5

Standardized and Unstandardized Regression Weights for the Mediation Model

Model	Estimate	S.E.	C.R. (Wald Statistic)	p	St. Estimate
OHC Participation → Identification with the Community	.328	.08	3.18	.004	.33
OHC Participation → Interpersonal Bonds with other Members	.22	.08	.97	.037	.18
OHC Participation → Perceived Social Support	.04	.06	2.14	.79	.04
Identification with the Community → Perceived Social Support	.317	.10	1.04	.002	.26
Interpersonal Bonds with other Members → Perceived Social Support	.17	.08	1.13	.042	.12

Chapter Summary

In this chapter, I conducted a cluster analysis to classify users' participation into four categories (Study One): hybrid mode posting, task-mode posting, relational mode posting, and task mode lurking. Additional ANOVAs on these user-participation types yielded significant variation among the three major factors involved in the confirmed mediation model. For *Study Two*, I examined the proposed mediation model using structural equation modeling. The results indicated that identification with the community and interpersonal bonds with other community members served as two mediators in the relationship between OHC participation and perceived social support. In the next chapter, I discuss meaningful findings from this study regarding their contribution to communication literature on online health communities. I also discuss implications for research.

CHAPTER 5: DISCUSSION

Past research on OHC demonstrates a need to better understand the complexity of people's OHC participation as well as mechanisms underlying the participation-social support link. The goal of *Study One* was not only to conceptualize participation in two equally important dimensions (i.e., level & mode) but also to validate such conceptualization via an empirical-based typology development. The findings represent important contributions to the body of OHC research by showing characteristic patterns of OHC participation that can be measured, which provides a basis for the second study.

The critical advance that *Study Two* provides is to demonstrate the mechanisms through which members' OHC participation influences their perceived social support. Previous research on OHC has suggested mixed findings on the impact of OHC participation on users' health outcomes, but those results are incomplete and do not explain the mechanisms underpinning the relationship between participation and perceived social support (a robust predictor of beneficial health-related outcomes). Drawing on Prentice et al.'s (1994) common-identity and common-bond framework, I argue that identification with the community and interpersonal bonds with others are the missing mechanisms (for the purpose of brevity, I use identification and interpersonal bonds thereafter). Results support a mediation model that suggests perceived social support flows from both identification and interpersonal bonds engendered by participation in OHCs. Specifically, I found identification has a stronger mediating effect than interpersonal bonds. Furthermore, the current findings indicate that identification,

interpersonal bonds, and perceived social support vary across different user participation types (as identified in *Study One*).

In this chapter, I further explore each study's findings that jointly compose the major contributions of this dissertation. I follow this elaboration by discussing some limitations to this study. Lastly, I conclude this dissertation by establishing an agenda for future research that builds upon findings presented in Chapter 4.

Study One

The advent of Web 2.0 allows people facing a new diagnosis, undergoing treatment, or living with chronic illness to engage within larger networks. Yet little is known about which segments of users are inclined to make robust use of such information technology and which are not. With that in mind, *Study One* was guided by a desire to find a quantitative means to analyze OHC participation while simultaneously considering the many different participation patterns people form and create. I critiqued previous methodological approaches as limited by a static conceptualization of participation that dichotomized people's online interaction (e.g., low participation vs. high participation) that did not allow for variability of OHC participation. Specifically, I drew upon theoretical guidance from group communication researchers' work on task mode and relational mode (Beck & Keyton, 2014; Keyton 1999) to emphasize the importance in conceptualizing behavior in terms of goals and objectives.

In *Sorting Things Out*, Geoffrey C. Bowker and Susan Leigh Star explore the role of categories and standards in shaping the modern world. They argue that typology

development is powerful “technology” that represents certain social and technical choices as well as practical implications (Bowker & Star, 1999). User typologies organize complex participatory behaviors into meaningful characteristics patterns. A user typology of OHC conceptualizes participation as a complex human activity that varies across a range of dimensions. Following this approach, the main contribution of *Study One* to previous research is the identification of a fourfold typology of user participation (hybrid-mode posting, task-mode posting, relational-mode posting, and task-mode lurking) based on two distinct elements: level of participation (posting vs. lurking) and mode of participation (task and/or relational mode). Below, I elaborate on the identified patterns of user participation.

Hybrid-Mode Posting

Hybrid-mode posting refers to participatory behaviors that are active in both task-oriented posting and relational-oriented posting. Indeed, user participation categories might not be mutually exclusive (Bowker & Star, 1999; Brandtzaeg, 2010). As Douglas stated (1976), “individuals do not live in total isolation, and their scheme will be partially received by other individuals” (p. 54). Hybrid mode posting focuses on information seeking and providing as well as relationship building with other users. Users in hybrid-mode posting typically start out as the most active users. They tend to frequently read new posts in the community and engage in discussions, while offering emotional understanding to comfort other members and fostering online friendships. Those users may eventually grow into role models from whom other community members seek

advice and guidance (Lu, Jerath, & Singh, 2013). As support providers, they not only make direct efforts to provide relevant information and solve problems causing the stress, but also making other members feel cared through introduction, expressions of congratulations, sympathy, and encouragement.

Task-Mode Posting and Relational Mode Posting

Task-mode posting and relational-mode posting reflects the two determinants of successful online communities: usability and sociability (Preece, 2001). Usability describes the nature of task-mode posting, which reflects the capability of an OHC to be used easily and effectively by individuals to fulfill their tasks (Shackel, 1991). Task-mode posting is centered around the transmission of information, suggestions, or guidance (e.g., reading existing posts, engaging in discussion). This mode can be manifested in the form of describing types of problems, what to expect in different situations, solving the problems, recommendations, suggested approaches, or referrals to information resources. Scholars have agreed that task-mode posting is driven by several motives such as learning skills, offering expertise, and receiving responses from the community (Allison et al., 2011; Burke, et al., 2009; Wang, et al., 2011).

Alternatively, sociability describes the nature of relational-mode posting, which is related to interactions among community members through the supporting technology (Preece, 2001). Users in relational mode tend to engage in online interaction through cultivating interpersonal relationships (e.g., introducing a newcomer to the community, organizing community activities, and engaging in private messaging with other users).

Such relationships develop through the online exchange of sympathies and encouragements. Their participation is driven by a few motives: to achieve enjoyment in interacting with others, get emotional support, and be a group member (Nonnecke et al., 2006; Tedjamulia et al., 2005).

Task-Mode Lurking

For task-mode lurking, the findings indicate that those users are only interested in seeking information that meet their needs, such as seeking for answers on a question and following discussion topics. They barely engage in any reciprocity with others in the community. One reason may be the asynchronous communication of OHCs. There is no commitment and pressure for real-time interaction and members can either read, post or reply to messages at their convenience (Coulson & Knibb, 2008); or if they do not like participating, they can simply read stored conversations from other users (Walther & Boyd, 2002). In accordance of the social loafing perspective (Kollok & Smith, 1996), task-mode lurking can be described as a solitary, disconnected, unproductive action. Alternatively, the findings also show that task-mode lurkers oftentimes followed other active members' feed and added them in their community network. This created a "vicarious learning" (or "observational learning"; Shettleworth, 2010) environment for lurkers to understand how their active peers would approach questions rather than answering questions themselves. Consistent with Muller's (2011) argument, lurking is a "fundamentally social activity that occurs in a social context, that often involves other people, and that makes contributions to the social worlds of readers, authors, and the

organizations” (p. 291). In that sense, lurkers’ digital footprints (e.g., reading history manifested on a OHC page) may let the active posters believe that someone is consuming the contents they generated, which ultimately encourage posters to contribute more contents (Markus, 1990).

Practical Implications

Generally speaking, OHCs are faced with user attrition problems similar to other social media platforms where user migration occurs unless tailored contents and appropriate socialization is widely adopted (Huh et al., 2016). Identifying users’ typology of participation can provide OHC managers and practitioners with suggestions on how to sustain continued participation. For example, when introducing new community features (e.g., visualization techniques, new navigation system), it would be critical to attend to the experiences of relational-mode posters and task-mode lurkers separately. In the current research, relational-mode posters are more concerned with fostering interpersonal relationships while task-mode lurkers are interested in “getting things done”. The design of OHCs needs to be sensitive to the reactions of users with different participation patterns.

Study Two

This study provides a parsimonious framework for describing how OHC participation relates to group communication mechanisms (identification and interpersonal bonds) and support-related outcome (perceived social support). More specifically, it extends prior research using Prentice et al.’s (1994) common-bond and

common-identity approach (e.g., Dholakia, Bagozzi, & Pearo, 2004; Postmes et al., 2002; Ren et al., 2007; Sassenberg, 2002; Utz, 2003) by empirically examining different participation types that lead to two group communication mechanisms and how these mechanisms in turn influence users' perceived social support. Theoretically, the findings highlight the centrality of group communication mechanisms in OHCs, and, in so doing, strengthens the case for using identification and interpersonal bonds to understand how different patterns of OHC participation drive social support outcomes and how to draw on them as a resource to eventually improve people's health.

The Mediating Effect of Identification and Interpersonal Bonds

In accordance with previous studies, OHC participation is positively related to perceived social support through identification (with the community) and interpersonal bonds (with other members). Focusing on the mediating effect of identification, this study demonstrates that actively participating in online interactions can expedite people's identification process, which leads to increased perceived social support. Past scholarship has posited that when people communicate in a computer-mediated context, their perceptions of group identities are magnified, and perceptions of individual identities are reduced (Postmes et al., 1998; Walter, 2018). The salience of group identities connotes a psychological connection between self and the collective self, which leads individuals to ascribe group-defining characteristics to the self and to take the collective interest to heart (Turner et al., 1987). As a result, OHC members may perceive that social support from the community is available during their time of need.

Regarding the mediating effect of interpersonal bonds, this study showed that social support is delivered through social relationships (Cohen et al., 2000), and OHCs, are participatory platforms that thrive on creating and maintaining those relationships (Hether et al., 2014). Interpersonal bonds can be well developed and sustained in online communities through prolonged contact and continued communication (Lea & Spears, 1995; Postmes, Spears, & Lea, 2000; Walther, 1996). As shown in Keyton's (2009) model of relational communication in groups, such a relationship building process is reiterative and manifested in very personal thoughts or experiences related to themselves and their lives. People might disclose secret identities, emotions, wishes, or fears; they might also provide timely support to others with kindness and generosity. These relational interactions all contribute to the development of interpersonal intimacy and bonding (Barak et al., 2008) and the transformation of online weak-ties into a strong-tie network of similar others (Hass et al., 2010), which consequently help OHC users cope more effectively with stressors (Frost & Massagli, 2008; Shaw et al., 2000).

More importantly, the findings of this study indicate identification is the primary driving force for users' perceived social support compared to interpersonal bonds. This result echoes with Ren and colleagues' (2012) study, in which they find community features designed to foster group identification had stronger effects on user participation and retention than features intended to enhance online interpersonal friendships. In a similar fashion, this study provided evidence consistent with claims from several studies that group ties are better predictors of social support compared with individual ties (e.g.,

Haslam et al., 2010; Haslam et al., 2014). Below, I provide two major explanations to elaborate on the particular contribution that identification makes to perceived social support over interpersonal bonds.

One explanation is that OHCs included in this study were organically formed, voluntary online communities. Due to the voluntary nature, OHCs are different from other communities that demand in-group interdependence (e.g., open-source software communities suggest users to work on team products together and meet team goals). Another explanation adapts an organizational viewpoint: OHCs can be described as an instrument of knowledge-sharing in organizations (Hara & Hew, 2006) or a platform that enables collaborative work on social support exchange (Ramanadhan et al., 2012). This line of research explains how attitudes and behaviors are influenced by the psychological link between an individual and his/her organization (Ashforth & Mael, 1989; Meyer & Allen, 1997; Rhoades & Eisenberger, 2002; Van Dick, 2004). OHCs create an organizational setting where users are more likely to form a sense of belongingness through collective environments. As depicted by Flanagin et al. (2006), OHCs are salient examples of collective action, a communicative phenomenon which typically include ingroup relationships, shared interests, and the integration, coordination, and/or synchronization of individual contributions.

Furthermore, results from this study also speak to important relationships between key factors for measuring the sustainability of OHCs. To enhance the theoretical understanding of voluntary participation in online communities, Preece (2001) proposes a

success metric with several dimensions: commitment (affective attachment to the community), participation (number of visits, hits, logins), relationship development (extent of contact between members), and contributions (number of messages posted per period). Based on the fully-supported mediation model, this study showed users' participation and contribution can potentially predict commitment as well as relationship development, thereby enhancing the understanding of important relationships within the success metric for building sustainable OHCs.

Revisiting the Model by Accounting for Different Types of User Participation

Nonnecke and Preece (1999) contend that a strong sense of community can be developed even without active posting, which means it is possible that lurkers may develop a strong sense of identification with the community simply by lurking. Similarly, Nonnecke and Preece (2003) posit that “the non-reciprocal relationship of the poster and the lurker provides a sense of community for the lurker, even if it bends the concept of communities being reciprocal in nature” (p. 128). Those claims correspond with the findings of this study: all participation patterns are significantly associated with the identification with the community, yet posters (including hybrid mode, task mode, and relational mode) reported greater identification than lurkers. Indeed, scholars have argued that active participation may expedite people's identification process (Miller & Jablin, 1991). Compared with passive lurkers, proactively taking part in an OHC (e.g., visit the community more often, stay online longer per visit, post more messages, and are more

engaged in contributing to the online community than average) help members build a stronger sense of belongingness, affiliation, and social cohesion.

This research also confirmed that relational-mode posting (including hybrid mode and relational mode posting) leads to greater level of interpersonal bonds with other community members compared with task mode posting (including task mode posting and task mode lurking). Many individuals participate in an OHC to reduce feelings of loneliness and social isolation (Barak et al., 2008). Compared to other online communities built upon various purposes, OHC users have stronger desires to connect with similar others who are concerned and feel stigmatized (Batenburg & Das, 2015). Anonymity and absence of physical appearance reduce the amount of OHC users' nonverbal cues that may impede the development of interpersonal bonds, such as racial or sexual discriminations (Rains & Wright, 2016). With that, people are likely to feel more comfortable to share sensitive health information or stigmatized topics (Shaw et al., 2000). As such, relational-mode posting offers room for users to disclose their disturbing experience and vent negative emotion, which provides a basis for building trust and meaningful interpersonal relationships (Joinson & Paine, 2007).

Another important finding in *Study Two* is that both users in hybrid-mode posting and relational-mode posting reported greater perceived social support than task-mode lurking; no difference was found between task-mode posting and task-mode lurking in terms of perceived social support. As relational mode is salient across hybrid-mode posting and relational-mode posting, this finding demonstrates the unique impact that

relational-oriented posting exerts on users' perceived social support. Research has shown that relational mode posting typically consist of messages that (1) share similar difficulties, misery, or distress (Helgeson & Gottlieb, 2000) and (2) deliver love, empathy, caring, and trust (Cobb, 1976; Keyton, 1999), which leads individuals to believe they are cared for and loved, valued, and will have support during times of need.

Practical Implications

As stated in the study rationale (see Chapter 1), understanding what group communication mechanisms influence OHC users' health-related outcomes is an important factor in determining the value and effectiveness of OHCs to support breast cancer patients. Social support is an inherently communicative behavior that helps people reduce uncertainties and enhances perceptions of control over the stressful situation (Albrecht & Adelman, 1987; Cline, 1999). Findings of this study can inform the design of OHCs to provide targeted social support to help users achieve better health outcomes, such as reduced stress and depression level, improved quality of life and well-being. Moreover, connecting different participation types with social support serves as a personalized therapeutic modality that helps users with information acquisition, problem solving, and the development of coping strategies.

Limitations

This dissertation project is not without limitations. Below, I describe how my sample, study design, survey, measurement, and data decisions limit the findings of this study. First, since there was no available public data regarding the frequent usage and

popularity of OHCs, I selected communities based on publicly available information collected for this study, including community descriptions, news reports, peer-reviewed publications, and third-party white papers. The inclusion criteria (data was collected from 12 OHCs) might compromise the generalizability of the findings. Moreover, it was difficult to gain the approval of several OHC moderators to post the survey recruitment message. Some communities refused to post the recruitment flyer with the concern of “protecting” their members. Other sites allowed the message to be posted but only in a forum specifically singled out for solicitations, which might impede OHC users from seeing the recruitment message.

Second, *Study One* suggests that people have different orientations for OHC participation—such as information seeking and relationship building—but these orientations have been found to change over time (Kim, 2000; Normid, 2012; Rodgers & Chen, 2005). Studying the change of user orientations requires longitudinal research. What is missed from this project is the longitudinal perspective that illustrates how an individual changes participation patterns over time. People may transition from lurker to poster, low task mode to high relational mode. These transitions may be influenced by their stages of illness management, behavioral change, and evolution of interpersonal relationships with other community members over time.

Third, survey research has limitations which include self-report bias and lack of representativeness. It is conceivable that survey respondents in this research might report answers in a way that they deemed to be more socially acceptable than would be their

“true” answers. Moreover, respondents who identified with their online community might be more willing to join the research than others. This self-selection could bias the analysis by inflating the effect of identification with the community.

Fourth, the measurement suggested in this study does not yield an absolute typology of people’s OHC participation. The OHC landscape, users, and participatory behaviors continuously evolve. Thus, there is a possibility that dimensions of an individual’s participation mode were oversimplified in my conceptualization. In addition to task mode and relational mode, other modes might exist to compound the findings, such as providing and receiving social support.

Fifth, it is important to note that the survey data was collected from users across 12 OHCs, and approximately one third of the participants ($N = 107$) did not specify with which community they are affiliated. Thus, it is not possible to compare the difference of responses provided by participants from various communities (12 communities in this dissertation project). This is important to note because the 12 different OHCs varied in size, communication features, and activity flow. However, all of these communities were specifically focused on breast cancer support. Future studies should capture data on the specific OHCs where people participate and perform a series of configural and metric invariance tests using confirmatory factor analysis (CFA) to investigate whether the survey data collected from different communities are invariant among major variables proposed in the mediation model.

Lastly, it is important to note that SEM cannot predict direction and confirm causal dependencies between endogenous and exogenous variables (Hoyle & Smith, 1994). In other words, SEM analysis can only be used to infer causality. Relevant variables can also exert reciprocal influence rather than expecting causality to flow exclusively in one direction. Therefore, it is possible that the opposite direction is also accurate in the mediation model. For example, I interpreted OHC participation as a factor that positively predicts identification with the community; however, it could be that the sense of belongingness and oneness motivates members to participate in community activities. Similarly, the model may work in a cyclical fashion: perceived social support affects continued participation, which, in turn reinforces identification and interpersonal bonding, and so forth.

Future Research Agenda

This dissertation provides several directions for future research. Here, I discuss four avenues for additional studies that continue this line of research: (1) strong-tie/weak-tie support-network preference, (2) dimensions of a stressor and social support types, (3) diverse sample facing chronic diseases, and (4) relevant theoretical models.

To begin, scholars should further explore how users' preferences of using OHCs influence participation patterns. Wright and Miller's (2010) seminal work on strong-tie/weak-tie support-network preference proposes four factors—objectivity, utility, comfort, and risk—that influence an individual's decision to use online weak-tie support-networks as an alternative resource of social support. Understanding the relative

importance of the four preferences of using weak-tie support-networks in predicting different participation patterns has important implications for theory development and model testing. Moreover, researchers are encouraged to move beyond characterizing participation of online communities to blend online and offline interactions, such as comparing online group ties, online individual ties, offline groups ties, and offline individual ties.

Second, subsequent studies may seek to match different participation types with dimensions of a stressor as well as various types of social support. Cutrona and Russell (1990) coined the optimal matching model to explain how social support operates in interactions. They contend that social support is most beneficial when it matches a person's stressor. More specifically, the model posits that matching the five types of social support (i.e., informational, emotional, esteem, network, and tangible support) with the dimensions of a stressor (i.e., controllability, life domain, desirability, duration of consequences, and stigma) produces the most positive outcomes (Cutrona & Russell, 1990). Building on this model, scholars interested in this work might consider (1) how OHC participation leads to different types of social support and (2) what stressors result in various participation patterns.

Third, future studies are encouraged to extend the current typology to understand different group communication mechanisms and support outcomes. *Study One* has shown how user participation types can be identified and understood within OHCs, whereas it is not clear if the mediation model established in *Study Two* still hold true among users in a

specific participation mode (e.g., if the task-mode lurking leads to identification with the community and interpersonal bonds with others, which in turn influence perceived social support). With this goal in mind, more extensive user studies with more sophisticated statistical analyses are recommended for future research.

Fourth, to understand the complexity in an increasingly fragmented user population, future studies should gain more knowledge on what participation types are linked to certain user characteristics (e.g., age, health conditions, digital literacy) in the general population. At the same time, instead of focusing on breast cancer patients, further research should look at how people facing chronic diseases leverage and expand their online social networks to navigate different user experiences, which can, in turn, inform the development of future interventions and resources that may supplement, or complement, traditional care.

Lastly, it is important to apply relevant theoretical models to test the rigor of the participation measure, such as the eight personality types (i.e., from extraverted sensing to introverted feeling; Jung, 1971), the diffusion framework (i.e., how, why, and at what rate people adopt new ideas and technological innovations; Rogers, 2003), and uses and gratification theory (i.e., motivations and gratification needs of why people use media; Katz, Blumler, & Gurevitch, 1974).

Conclusions

This dissertation attempted to fill the gap in the literature related to OHC participation and social support outcomes. In doing so, this dissertation used two

interconnected studies to extend the literature in three ways: (1) theoretically, by proposing and testing a mediation model to explain the participation-social-support link, (2) methodologically, by advancing a typology-based measurement of OHC participation, and (3) practically, by assessing the impacts of different participation types on social support outcomes. Together, these two studies help inform the understanding the complex role of OHC participation in empowering healthcare consumers thereby addressing calls from communication researchers to focus on the multidimensional use of health information technology (HIT).

Appendices

Appendix A: Consent for Participation in Research

Title:

Participation in Online Health Communities (OHCs) and Perceived Social Support:
Elaborating Participation Forms and Incorporating the Role of Identification along with Interpersonal Bonds

Purpose of the Study

Rooted in the context of online health community (OHC), the overarching purpose of this dissertation project is to propose and test a theoretical model that explains how two group communication mechanisms—identification with the OHC and interpersonal bonds with other members—mediate the relationship between users' OHC participation and their perceived social support.

What will you be asked to do?

If you agree to participate in this study, you will be asked to complete an online survey. This study will last no longer than 20 minutes.

What are the risks involved in this study?

There are no foreseeable risks to participating in this study.

What are the possible benefits of this study?

You will receive no direct benefit from participating in this study; however, the findings will provide recommendations for OHC design and cancer communication research, and for ways to improve OHC users' mental health and well-being.

Do you have to participate?

No, your participation is voluntary. You may decide not to participate at all or, if you start the study, you may withdraw at any time. Withdrawal or refusing to participate will not affect your relationship with The University of Texas at Austin (University) in anyway. You will receive a copy of this form.

Will there be any compensation?

You will have a chance to win a \$20 Amazon gift card as compensation. You will be responsible for any taxes assessed on the compensation.

How will your privacy and confidentiality be protected if you participate in this research study?

This study won't collect your identifiable information. Only the researcher of this study will have access to the information collected. Data will be protected by being saved on the researcher's password-protected personal computer. The data itself will not contain any identifiable information unique to you. Once the data is analyzed, raw data will be kept only for research purpose.

If it becomes necessary for the Institutional Review Board to review the study records, information that can be linked to you will be protected to the extent permitted by law. Your research records will not be released without your consent unless required by law or a court order. The data resulting from your participation may be made available to other researchers in the future for research purposes not detailed within this consent form. In these cases, the data will contain no identifying information that could associate it with you, or with your participation in any study.

Whom to contact with questions about the study?

Prior, during or after your participation you can contact the researcher Yaguang Zhu at 512-239-9931 or send an email to yaguang.zhu@utexas.edu for any questions or if you feel that you have been harmed.

Whom to contact with questions concerning your rights as a research participant?

For questions about your rights or any dissatisfaction with any part of this study, you can contact, anonymously if you wish, the Institutional Review Board by phone at (512) 471-8871 or email at orsc@uts.cc.utexas.edu.

By clicking on the ">>" button below, you are indicating agreement with the following claim:

I have read the above information and have sufficient information to make a decision about participating in this study. By clicking on ">>," I am giving my consent to participate in the study.

Thank you in advance for considering participation in this study.

Please print a copy of this document for your records.

Appendix B: Recruitment Flyer

Participants Needed!



The University of Texas at Austin
Communication Studies
Moody College of Communication

for a dissertation study on Online Health Communities

We are looking for breast cancer patients who would like to participant in research!

For more information please e-mail:

Yaguang Zhu, M.A.

yaguang.zhu@utexas.edu

Participants who complete their survey will be put into a lottery with a chance for three people to win \$20 Amazon gift card.

Participants will be asked to:

Complete a web-based survey on Online Health Communities

The information we find out in this study will be used to better understand people's use and the design of online health communities.

Appendix C: Survey Instruments

Section 1: Online Health Community (OHC)

Instructions: Please think about the online health community that you use the most frequently and answer the following questions:

1. What is the online health community that you use the most frequently?
 - A. American Cancer Society
 - B. Facebook group
 - C. HealthBoards
 - D. Health Union
 - E. HealthUnlocked
 - F. MedHelp
 - G. PatientLikeMe
 - H. Sharing Mayo Clinic
 - I. Twitter group
 - J. WebMD
 - K. Others_____ (please specify)

2. How do you access your OHC account? (you can choose more than one)
 - A. PC (personal)
 - B. PC (library or public computer)
 - C. Laptop
 - D. Smartphone
 - E. iPad/iPod
 - F. Others_____ (please specify)

3. How long have you been using the OHC?
 - A. Less than a week
 - B. 2 weeks – 1 month
 - C. 1 months – 3 months
 - D. 3 months – 6 months
 - E. 6 months – 1 years
 - F. 1 years – 2 years
 - G. 2 years – 3 years
 - H. 3 years – 5 years
 - I. Over 5 years

4. How frequently did you visit the OHC in the past week?
 - A. Never
 - B. 1-2 times per week
 - C. 3-5 times per week
 - D. 1-2 times a day
 - E. Several times a day

5. In the past week, on average, approximately how many minutes per day have you spent on the OHC? (Ellison et al., 2007)
 - A. I didn't use the OHC
 - B. Less than 30 minutes
 - C. 30 minutes to 1 hour
 - D. 1 hour to 1.5 hours
 - E. 1.5 hours to 2 hours
 - F. 2 hours to 2.5 hours
 - G. 2.5 hours to 3 hours
 - H. 3 hours to 3.5 hours
 - I. 3.5 hours to 4 hours
 - J. More than 4 hours

6. About how many users do you think also participate in the OHC you use most often?
 - A. Less than 50
 - B. 50-100
 - C. 100-200
 - D. 200-500
 - E. Over 500

7. About how many "friends" do you currently have in the OHC? (Ellison et al., 2007)
 - A. 1-5
 - B. 6-10
 - C. 10-20
 - D. 20-30
 - E. 30-40
 - F. 40-50
 - G. Over 50

8. About how many of your "friends" on the OHC have you met in person?

- A. None of them
- B. A few of them
- C. About half of them
- D. Most of them
- E. All of them

Section 2: OHC Participation

Instructions: The following 28 statements are designed to examine your participation experiences with the online health community. For each item below, please circle the number that best indicates your opinion on the following scale.

1= Never; 2=Rarely (in less than 10% of the chances); 3=Occasionally (in about 30% of the chances); 4=Sometimes (in about 50% of the chances); 5=Frequently (in about 70% of the chances); 6= Usually (in about 90% of the chances); 7= Every Time

1. I read other people's post in on the site.
2. I post questions on the site.
3. I answer questions on the site.
4. I check announcement on the site.
5. I update my profile status on the site.
6. I post/share pictures on the site.
7. I post/share videos on the site.
8. I engage in discussions on the site.
9. I ask for suggestions on the site.
10. I give suggestions to people on the site.
11. I seek for new information on the site.
12. I follow discussion threads on the site.
13. I use the site for educational purpose.
14. I surf other people's profiles on the site.
15. I look for a new friend on the site.
16. I welcome new people on the site
17. I get in touch with new people on the site.
18. I write/chat with friends on the site.
19. I write/chat with acquaintances on the site.
20. I write/chat with strangers on the site.
21. I encourage people on the site.
22. I express my empathy to people's posts on the site.

23. I send private messages to others on the site.
24. I get contacted by other people on the site.
25. I check if somebody has tried to contact me on the site.
26. I run community groups on the site.
27. I arrange appointments with other people on the site.
28. I connect people with others on the site.

Section 3: Identification (Mael & Ashforth, 1992)

Instructions: Next, based on your experiences using the online health community, please indicate the extent to which you agree with the following statements.

1=Strongly disagree; 2=Disagree; 3=Somewhat disagree; 4=Neutral; 5=Agree; 6=Somewhat agree; 7=Strongly agree

1. When someone criticizes my community, it feels like a personal insult.
2. I am very interested in what others think about my community.
3. When I talk about this community, I usually say “we” rather than “they.”
4. This community’s successes are my successes. When someone praises this community, it feels like a personal compliment.
5. If a story in the media criticized this community, I would feel embarrassed.

Section 4: Interpersonal Bonds (Prentice et al., 1994)

Instructions: With the same community in mind, please answer the following questions.

1. How close do you feel close to the other members of your OHC?
2. How many members of your OHC have influenced your thoughts and behaviors?
3. How many of your friends come from your OHC?

Section 5: Perceived Social Support (Cutrona & Russell, 1987, 1990)

Instructions: Based on your experiences using the online health community, please indicate the extent to which you agree with the following statements.

1=Strongly disagree; 2=Disagree; 3=Somewhat disagree; 4=Neutral; 5=Agree; 6=Somewhat agree; 7=Strongly agree

1. There are people I can depend on in this online community to help me if I really need it.
2. I feel that I do not have close personal relationships with other people in this online community. (reverse coded)
3. There is no one I can turn to in this online community for guidance in times of stress. (reverse coded)
4. There are other people in this online community who depend on me for help. (reverse coded)
5. There are other people in this online community who enjoy the same social activities that I do.
6. Other people in this online community do not view me as competent. (reverse coded)
7. I feel personally responsible for the well-being of another person in this online community.
8. In this online community, I feel part of a group of people who share my beliefs and attitudes.
9. In this online community, I feel part of a group of people who respect my skills and abilities.
10. If something went wrong, no one in this online community would come to my assistance.
11. I have close relationships with people in this online community that provide me with a sense of emotional security and well-being.
12. There is someone in this online community I could talk to about important decisions in my life.
13. I have relationships in this online community where my competence and skills are recognized.
14. There is no one in the online community who share my interests and concerns. (reverse coded)
15. There is no one in the online community who really relies on me for their wellbeing. (reverse coded)
16. There is a trustworthy person I could turn to in this online community for advice if I were having problems.
17. I feel a strong emotional bond with at least one other person in this online community.
18. There is no one I can depend on in this online community for aid if I really need it. (reverse coded)
19. There is no one I feel comfortable talking about problems with in this online community.
20. There are people in this online community who admire my talents and abilities.

21. I lack a feeling of intimacy with another person in this online community. (reverse coded)
22. There is no one in this online community who like to do the things I do. (reverse coded)
23. There are people in this community I can count on in an emergency.
24. In this online community, no one needs me to care for them. (reverse coded)

Section 4: Demographic Information

*Instructions: Please fill in or mark the appropriate blanks below. We will **NOT** use or report information in such a way as to identify individuals based on their demographic characteristics or otherwise*

1. How old are you? _____
2. How would you describe yourself?
 - A. African American/Black
 - B. Asian American
 - C. Caucasian/White
 - D. Hispanic/Latina
 - E. Other:
3. In general, would you say that your health is____?
 - A. Excellent
 - B. Very good
 - C. Fair
 - D. Poor
 - E. Very Poor
 - F. Unsure
4. What is your marital status?
 - A. Single
 - B. Married
 - C. Divorced
 - D. Living with partner/significant other
 - E. Other:
5. What is your highest level of education achieved?
 - A. Some high school or less

- B. Completed high school
 - C. Some college/trade school
 - D. Completed college
 - E. Graduate school
6. Do you have a job (e.g. paid employment)?
- A. Yes, I have a full-time job outside the home
 - B. Yes, I have a part-time job outside the home
 - C. Yes, I have a job that allows me to work from home
 - D. I am a full-time student
 - E. No, currently I am not working
7. What is your annual household income? (Han et al., 2012; Han et al., 2014)
- A. Less than \$25,000
 - B. \$25,000 to \$49,999
 - C. \$50,000 to \$74,999
 - D. \$75,000 to \$99,999
 - E. \$100,000 or more
8. What state do you live in currently? _____

THANK YOU FOR YOUR PARTICIPATION. Your participation in this survey will result in both practical and theoretical findings that will contribute to scholarship in the communication field.

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