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Communicating Personal Health Information in Virtual Health Communities: An Integration of Privacy Calculus Model and Affective Commitment

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Abstract:

Health consumers such as patients and caregivers often join virtual health communities (VHCs) to seek and provide health-related information and emotional support. To do so, they converse with other individuals in platforms such as public discussion boards and blogs. During these online conversations, people may communicate their personal health information (PHI) to others. A potential driver for this form of revealing PHI is the immediate positive outcomes that it can provide for contributors and the community. PHI disclosure, however, can entail privacy risks and concerns for community members, which may ultimately hamper their participation in those communities. Moreover, one's emotional attachment to a VHC (namely, affective commitment) may influence one's PHI sharing behaviors in that community. Thus, to understand how various factors impact communicating PHI in public VHC discussions, we drew on the privacy calculus model and the notion of affective commitment, developed a theoretical model, and empirically tested the model. To do so, we administered a survey to individuals from three different populations including students, faculty, and staff at a large university and visitors to clinics. We performed a set of hierarchical moderated multiple regressions on the dataset. The results revealed that privacy concerns along with expected personal and community-related outcomes of communicating PHI affected willingness to communicate PHI in public VHC discussions. The results, however, refuted the hypothesized direct and moderating effects of affective commitment on willingness to share PHI in these virtual platforms. The findings of this study provide contributions to research and practice.

Keywords: Online Social Networks, Virtual Health Communities, Personal Health Information, Privacy Calculus, Affective Commitment, Self-disclosure, Health Communication.

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1 Introduction

In recent years, the use of social media technologies and platforms for health communication has grown significantly. A major reason for this growth is that people are increasingly relying on the Internet to find answers to their medical questions and to engage in online health-related discussions. A national survey conducted by the Pew Research Center showed that 25 percent of the respondents had looked at someone else's personal health experience and medical issues that were posted online, and 16 percent of the respondents had looked for other Internet users with similar health conditions in the last 12 months (Fox & Duggan, 2013). Moreover, 40 percent of the respondents indicated that they shared their health-related experiences online. In line with this trend, hundreds of social media-enabled, health-specific websites—also known as virtual health communities (VHCs)—have been developed. VHCs are "online environments in which users interact with one another around a set of common interests or shared purpose related to health using a variety of tools including discussion boards, chat, virtual environments, and direct messaging" (Newman, Lauterbach, Munson, Resnick, & Morris, 2011, p. 342). PatientsLikeMe.com, DailyStrength.org, and MedHelp.org are among the most widely used VHCs in the United States (Kordzadeh & Warren, 2013).

Healthcare organizations such as clinics and hospitals have also embarked on social media strategies by developing and offering VHCs for individuals (Kordzadeh & Young, 2015). Mayo Clinic pioneered the use of social media in the United States by establishing "Mayo Clinic Center for Social Media"[1] and initiating an online community[2] for health consumers to communicate with each other. Health consumers in this context refers to not only patients but also their caregivers and anyone in the community who seeks to maintain a healthy lifestyle (Payton, Pare, Le Rouge, & Reddy, 2011).

Health consumers who adopt social media technologies can become active participants in social support and health-related information exchange activities. This adoption is consistent with the notion of consumer health informatics (Payton et al., 2011; Wickramasinghe, Teoh, Durst, & Viol, 2013) and patient-centered e-health (PCEH) applications, which revolve around patients as pivotal actors in the healthcare ecosystem. Those applications focus on the three characteristics of health information systems: patient-focus, patient-activity, and patient-empowerment (Wilson, Wang, & Sheetz, 2014).

Individuals join VHCs to seek and provide emotional and informational support while interacting with other members of the community. Emotional support includes expressions of care, encouragement, empathy, and active listening; whereas informational support refers to providing health and wellness-centered information relevant to or of interest to peers in the community (Dale, Williams, & Bowyer, 2012; Dennis, 2003; Nambisan, 2011). The information may pertain to such areas as specific disease symptoms, treatments, medical procedures or to detailed information related to healthcare providers such as hospitals, clinics, and doctors (Alexander, Peterson, & Hollingshead, 2003; Demiris, 2006). Using VHC platforms, individuals can make social ties with others who are suffering from similar medical conditions or have undergone similar procedures (Chung, 2014; Lasker, Sogolow, & Sharim, 2005) and learn from their relevant knowledge and experiences (Kordzadeh, Liu, Au, & Clark, 2014). The practical advice and emotional support offered through these platforms may be more helpful than those obtained through formal sources of information that patients receive during physician and hospital visits (Grandinetti, 2000; Griffiths, Calear, & Banfield, 2009; McNair, Highet, Hickie, & Davenport, 2002). Thus, the cost-effectiveness, convenience, and the range of opinions and experiences that one can obtain from these online communities have made them effective channels for health communication (Chung, 2014; Cline & Haynes, 2001; Grandinetti, 2000).

Individuals who use VHCs can create profile pages on the community websites and post their personal images and information such as name, age, gender, and health conditions on these pages. Additionally, users can use various collaboration mechanisms and platforms that VHCs provide for health communications. Those platforms include health blogs, discussion boards, and physician-rating mechanisms (Kordzadeh & Warren, 2013; Newman et al., 2011; Scanfeld, Scanfeld, & Larson, 2010). Discussion boards are among the most widely used collaboration platforms in VHCs (Chung, 2014). Those platforms, also known as forums, enable individuals to initiate discussion topics, to seek support from the forum's community with respect to specific health issues, questions, conditions, and to post comments to others' topics (Evans, Donelle, & Hume-Loveland, 2012; Van Uden-Kraan, Drossaert, Taal, Seydel, & Van De Laar, 2009). Discussion boards are typically organized based on health conditions or support groups

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[1] http://network.socialmedia.mayoclinic.org

[2] http://connect.mayoclinic.org

(e.g., cancer, depression, migraines, and eating disorders). For example, DailyStrength.org provides more than 500 support groups in which users can participate by initiating discussion threads and responding to the threads initiated by other community members.

Participation and support exchange activities in public VHC discussions, however, may involve sharing personal health information (PHI). PHI includes information about one's diseases, health conditions, symptoms, treatments, medications, test results, and health-related experiences and emotions. Sharing PHI may raise privacy concerns for individuals who want to adopt those social media environments for health communications (Moorhead et al., 2013). In particular, PHI disclosure in publicly available communication platforms such as discussion boards may make people concerned about potential risks associated with this form of information disclosure. Those risks may range from social stigma and job loss to increased insurance premiums and unsolicited advertisements (Anderson & Agarwal, 2011; Beckerman & Foundation, 2008; Ziegeldorf, Morchon, & Wehrle, 2014). The privacy risks and concerns may eventually hamper active participation and effective adoption of VHCs, which may ultimately reduce the community’s success, prosperity, and growth over time.

Despite the presence of a level of privacy concern associated with PHI communication through social media environments, people still engage in this form of communication and actively seek and provide health-related knowledge while interacting with other individuals. A potential reason for this seemingly inconsistent behavior is the potential benefits of using VHCs, participating in health discussions, and communicating PHI in VHC platforms such as discussion boards. Those platforms provide individuals with access to a wealth of health information, particularly to those who may not conveniently access health information through traditional channels (Moorhead et al., 2013). However, in order to receive relevant and effective support from the community, one may need to discuss one’s specific medical conditions and experiences. Otherwise, the community members may not be able to provide aid that is specifically applicable to the support seeker’s situation. Moreover, in order to provide the community with helpful information and emotional aids, supporters may need to publicly discuss their personal experiences, medical conditions, and treatments, which, in fact, constitute their PHI. This disclosure may not only provide the community with benefits but may also provide the supporter with a level of relief and satisfaction with helping others. (Van Uden-Kraan et al., 2008).

Given the privacy costs and perceived benefits of communicating PHI in VHCs, VHC users who intend to engage in support exchange activities are faced with decisions between sharing and not sharing their PHI when communicating with others. On one hand, community members are willing to disclose their health information to the community to receive supportive comments and messages and also to help others in the community to whom this information can be useful. One the other hand, sharing PHI and publicizing it on these websites can result in unforeseen negative results for the information owner.

In this paper, we examine these two opposing factors in order to understand how perceived benefits and privacy costs can influence one's intentions to share PHI while communicating within VHCs. To do so, we draw on the notion of the privacy calculus model (Culnan & Armstrong, 1999). This model suggests that both contrary beliefs can act simultaneously and that the stronger belief can override the weaker one. Ultimately, the overriding belief determines if an individual is willing to engage in an information-intensive risky behavior such as disclosing personal information (Dinev & Hart, 2006). We discuss this theoretical model in Section 2.

The results of recent studies show that emotional attachment to online communities—namely, affective commitment (Ellemers, Kortekaas, & Ouwerkerk, 1999)—can positively influence individuals' participations in those communities (Ren et al., 2012; Tsai & Bagozzi, 2014). Accordingly, those who feel more attached to an online community participate more actively in that environment (Bagozzi & Dholakia, 2002; Bateman, Gray, & Butler, 2011a; Ren et al., 2012). In the context of VHCs, affective commitment can potentially affect users' intentions for communicating PHI to other individuals because affect and emotions play a major role in shaping peer-to-peer relationships. Consequently, these factors may impact the quality and quantity of the social support exchanged in virtual environments. Thus, we also examine the potential impact of affective commitment on PHI disclosure in VHCs.

Specifically, we address the following two research questions:

RQ1: How do expected positive outcomes and privacy concerns associated with PHI disclosure influence how individuals communicate their PHI in VHCs?

RQ2: How does affective commitment influence how individuals communicate their PHI in VHCs?

From a theoretical perspective, this study extends the privacy calculus model by incorporating affective commitment into the model and applying the extended model to the context of health communications in VHCs. The results of this study offer contributions to the literature primarily in the areas of information privacy, health informatics, and participation and self-disclosure in online communities. In particular, the findings provide theoretical implications along the three dimensions of context, content, and process of personal information disclosure. Prior studies that have employed the privacy calculus model to study personal information revelations have confined their research contexts to such areas as e-commerce transactions (Dinev, Bellotto, Hart, Russo, & Serra, 2006; Dinev & Hart, 2006) and social network sites (SNSs) (Acquisti & Gross, 2006; Krasnova, Kolesnikova, & Guenther, 2009; Scanfeld et al., 2010), whereas few research studies have focused on privacy and PHI disclosure in the context of VHCs. In this study, we apply an extended privacy calculus model to the VHC context.

Prior research on personal information disclosure in online communities and SNSs has not specifically distinguished health-related content from other types of personal information such as phone numbers, relationship statuses, and financial information (Acquisti & Gross, 2006; Gross & Acquisti, 2005). However, one needs to distinguish them because of PHI’s inherent sensitivity and the different potential privacy risks and negative consequences associated with publicizing PHI compared with publicizing other types of personal information (Williams, 2010; Xu, Dinev, Smith, & Hart, 2011). This sensitivity may influence individuals’ information-sharing behaviors in online environments. Thus, in the current study, we help to fill this gap by focusing specifically on the PHI privacy and sharing intentions in VHCs. Finally, the extant literature has addressed sharing personal information through the processes such as online shopping (Dinev & Hart, 2006) and creating and updating personal profile pages in SNSs (Gross & Acquisti, 2005). Given that the primary mission of VHCs is to facilitate computer-mediated communications among health consumers, we specifically focus on the process of disclosing PHI while communicating through public VHC discussions.

From a practical standpoint, our findings offer benefits for VHC providers and healthcare organizations that adopt social media strategies and intend to establish VHCs for their patients to communicate. Understanding the determinants of PHI disclosure in VHCs can help community providers address individuals' privacy concerns, improve perceived benefits of communicating PHI in public discussions, and promote active participation in VHCs. This participation can ultimately lead to the growth, vibrancy, and success of those virtual communities. Moreover, the results of recent studies show that adding social components to information systems can enhance acceptance and adoption of those technologies by users (Junglas, Goel, Abraham, & Ives, 2013). Thus, our findings benefit developers and providers of traditional healthcare information systems (e.g., electronic health records) that have incorporated or plan to incorporate socially enabled features and community platforms into those information systems. Furthermore, the results of this study provide benefits for governmental organizations such as the U.S. Department of Health and Human Services, which enforces privacy regulations such as the Health Insurance Portability and Accountability Act (HIPAA). Understanding privacy concerns and behaviors in virtual environments can help these organizations extend the privacy rules and regulations to help protect individuals' PHI that are shared in online communities.

This paper proceeds as follows. In Section 2, we discuss the study’s theoretical background and review the extant literature relevant to this research. In Section 3, we present the hypotheses and research model. In Section 4, we explain the research method we used in this study. In Section 5, we discuss the results of the different sets of analysis conducted on the dataset. In Section 6, we summarize the findings and discuss our findings, implications, limitations, and areas for future research. Finally, in Section 6, we conclude the paper.

2 Theoretical Background

2.1 Privacy Calculus Model

Researchers have defined information privacy in many ways. More recent discussions about information privacy suggest that it refers to one’s ability or desire to control information or have some influence over data about themselves (Bélanger & Crossler, 2011; Bélanger, Hiller, & Smith, 2002; Stone, Gardner, Gueutal, & McClure, 1983). Researchers have long cited the protection of information privacy as a major challenge and potential threat associated with creating, using, storing, and sharing personal information (Bélanger & Crossler, 2011; Pavlou, 2011; Smith, Dinev, & Xu, 2011; Xu et al., 2011). In recent years and with the growth of social media, information privacy and understanding how to protect it in online environments have become very critical. Disclosing personal information in any form of SNSs makes users vulnerable to various types of privacy risks (Xu, Michael, & Chen, 2013). These risks depend on the identifiability of the information provided, possible recipients, and possible uses of the information disclosed on those networks (Gross & Acquisti, 2005; Jiang, Heng, & Choi, 2013). The major privacy risks cited in the extant literature are identity theft (Gross & Acquisti, 2005; Lo & Riemenschneider, 2010; Nosko, Wood, & Molema, 2010), cyber stalking (Nosko et al., 2010; Palfrey, 2008; Stutzman, Capra, & Thompson, 2011), physical stalking (Gross & Acquisti, 2005), price discrimination, unsolicited advertising (Gross & Acquisti, 2005; Ziegeldorf et al., 2014), and blackmailing (Gross & Acquisti, 2005; Stutzman et al., 2011). Moreover, information disclosure can result in negative social consequences such as damaged reputation and social standing due to rumors and gossip (Debatin, Lovejoy, Horn, & Hughes, 2009; Krasnova et al., 2009), negative impacts on one's sense of worth (Krasnova et al., 2009), and stigmatization, particularly for minority groups (Nosko et al., 2010).

Despite the potential risks associated with personal information disclosure in different contexts, people continue to share their personal information when communicating with others in online or offline environments or when conducting business transactions. Prior literature explains this inconsistent behavior and suggests that, although personal information disclosure may raise a level of privacy risks, that disclosure may in return provide the information owner with tangible (Xu, Teo, Tan, & Agarwal, 2009) or intangible (Dinev & Hart, 2006) benefits. Those potential benefits may drive individuals to engage in risky privacy behaviors (Jiang et al., 2013). The trade-off between privacy and benefits of information disclosure along with the outcome of this trade-off constitute the notion of privacy calculus model (Culnan & Armstrong, 1999). Culnan and Armstrong (1999) first coined this model, and Culnan and Bies (2003) further elaborated on it. The authors of these papers argue that individuals are willing to disclose personal information in exchange for social and economic benefits. In the business contexts, customers disclose personal information and continue to do that if they perceive this disclosure provides benefits for them that exceed the current and future risks of information disclosure (Culnan & Bies, 2003).

Privacy calculus is built on the notion of calculus of behaviors. According to the calculus of behaviors, institutional norms, anticipated benefits, and unpredictable consequences lead to an individual's decision on disclosing personal information (Laufer & Wolfe, 1977). Privacy calculus is also consistent with a widely used economic technique called cost/benefit analysis (Culnan & Bies, 2003). Cost/benefit analysis is used for evaluating the costs and benefits of a course of action in monetary terms to decide on whether to follow that course of action or not. This technique, however, has been extended to non-monetary contexts and adopted in other disciplines (e.g., Stone & Stone, 1990). Moreover, privacy calculus model is in line with the expectancy theory (Dinev & Hart, 2006). This theory postulates that people engage in a behavior if the expected positive outcomes of the behavior overweigh the expected negative outcomes (Porter & Lawler, 1968; Vroom, 1964).

Over the past years, researchers in different disciplines have adopted the privacy calculus model to study information disclosure in different information-intensive domains ranging from location-based services (Xu et al., 2009) and government surveillance (Dinev et al., 2006) to e-commerce transactions (Dinev et al., 2006; Dinev & Hart, 2006). In the context of e-commerce, Chellappa and Sin (2005) adopted the privacy calculus model to examine personalization services available to the Internet users. They investigated the trade-off between privacy concern and the value of personalized products, services, or the experiences associated with them and found that privacy concern and personalization value simultaneously affected one's intentions to use personalization services. Dinev and Hart (2006) adopted the privacy calculus perspective to examine the antecedents to behavioral intentions of personal information disclosure (e.g., credit card information, contact numbers, identifiers, etc.) in online transactions such as online purchasing or website registration. Consistent with the privacy calculus model, their findings demonstrated the impact of contrary beliefs (privacy concerns and privacy risks as the inhibitors and personal internet interest as the driver) on customers' willingness to disclose personal information over the Internet.

In the healthcare context, Anderson and Agarwal (2011) adopted the privacy calculus model to examine the circumstances under which patients are willing to disclose their identified PHI and permit others to digitize it. In that study, privacy concern and trust in electronic medium represented costs and benefits associated with information disclosure, respectively. The researchers conducted a scenario-based quasi-experimental study and found that the impact of privacy concern and trust on willingness to provide access to PHI was moderated by the requesting stakeholder (doctors/hospital, the government, and pharmaceutical companies) and by the purpose for which the PHI was requested (patient care, research, and marketing).

Other researchers have adopted the notion of privacy calculus to investigate the simultaneous impacts of perceived benefits and perceived privacy costs on information disclosure in SNSs. Debatin et al. (2009), for instance, found that perceived benefits of using Facebook exceeded privacy concerns of information disclosure. The results of a survey administered to Facebook users by Krasnova et al. (2009) demonstrated that privacy concern as the cost and perceived enjoyment as the benefit of information disclosure influenced the amount of self-disclosure on Facebook. Krasnova, Spiekermann, Koroleva, and Hildebrand (2010) further extended the benefits side of privacy calculus model and found that, among the hypothesized perceived benefits of information disclosure in SNSs, convenience, relationship building, and enjoyment significantly influenced one's self-disclosure, while self-presentation did not impact it. On the costs side, their results revealed that perceived privacy risk was a significant impediment to self-disclosure in SNSs.

Jiang et al. (2013) found that privacy concerns and social rewards simultaneously affected self-disclosure in synchronous online social interactions. Similarly, Xu et al. (2013) conducted a survey study in a Chinese university and found that privacy concern and perceived benefits of personal information disclosure influenced privacy disclosure in SNSs. Also, Zhao, Lu, and Gupta (2012) studied disclosure intentions of location-related information (e.g., current location, photographs, and description of surroundings) in location-based SNSs. They decomposed perceived benefits of information disclosure in this context into extrinsic benefits (personalization) and intrinsic benefits (connectedness) and demonstrated that both of those factors positively impacted intentions of information disclosure in SNSs, whereas privacy concerns negatively impacted information disclosure intentions in SNSs.

In summary, prior studies have demonstrated the rigor and robustness of the privacy calculus model in investigating and understanding simultaneous impacts of drivers and barriers to information disclosure in various information-intensive contexts. These contexts included areas such as healthcare (Anderson & Agarwal, 2011) and general-purpose SNSs (e.g., Krasnova et al., 2010; Krasnova & Veltri, 2010; Xu et al., 2013). To the best of our knowledge, no published research has specifically employed the privacy calculus model to examine PHI disclosure behaviors in VHCs. Nonetheless, several researchers have examined privacy concerns, the benefits of adopting and participating in VHCs, and sharing PHI with others in health social media environments. We discuss these studies in Section 2.2.

2.2 Privacy Calculus in VHCs

Information disclosure in social media environments may raise privacy violation risks and concerns. Those concerns may be even more critical when it comes to PHI (Moorhead et al., 2013). PHI-specific privacy concerns may:

> *span the gamut from financial anxiety (e.g., I don't want to be put into a high risk, high premium insurance plan), to embarrassment (e.g., I'm ashamed to tell [others] about my past risky behaviors), to job security (e.g., my employer might fire me if they know I have had a history of mental illness), to control (e.g., I don't want pharmaceutical companies marketing new drugs to me)* (Angst & Agarwal, 2009, p. 348).

Disclosure of certain types of information such as mental illness, substance abuse, and genetic traits may also result in social stigma, discrimination, criminal prosecution, and job loss (Anderson & Agarwal, 2011; Beckerman & Foundation, 2008).

Prior studies, however, demonstrated that joining and participating actively in VHCs can empower patients (Barak, Boniel-Nissim, & Suler, 2008; Merolli, Gray, & Martin-Sanchez, 2013) and provide them with positive mental, physical, and behavioral outcomes such as improved psychological wellbeing (Batenburg & Das, 2014), improved health-related behaviors (Wickramasinghe et al., 2013), and feeling less isolated (Powell, McCarthy, & Eysenbach, 2003). Prior studies have also suggested that the empathy perceived by patients in VHCs has the potential to expedite the healing processes and improve the effectiveness of treatments (Nambisan, 2011). Evans et al. (2012) conducted a content analysis on the messages posted in a disease-specific online support group and concluded that those virtual communities can enable women experiencing postpartum depression to make connections with others and receive useful information, encouragement, and hope through virtual communications with others. Active participation and knowledge dissemination in VHCs can also benefit caregivers in that their participation in online health forums can attenuate the negative effect of caregiver strain on their wellbeing (Tanis, Das, & Fortgens-Sillmann, 2011).

Previous research also suggests that people care about other individuals and may participate in online health-related discussions to provide benefits to them. For instance, Chung (2011) investigated individuals' participations in VHCs and found that helping others was one of the major motivations for joining VHCs and contributing in them. Oh (2012) found that altruism was the most influential motivation for answering others' health-related questions in social media platforms. These results are consistent with the findings of prior studies on non-health related virtual communities, which suggest that community-related outcome expectations can significantly impact the quality and quantity of the knowledge shared in those communities (Chiu, Hsu, & Wang, 2006). Therefore, the privacy concerns, along with the benefits of PHI disclosure in online environments, indicates that the privacy calculus model is an appropriate theoretical perspective that one can use to help understand how opposing factors impact individuals' PHI sharing behaviors while engaging in public discussions in VHCs.

2.3 Affective Commitment

Affective commitment is a theoretical concept that has long been of interest to researchers in the areas of organizational behavior and social psychology as well as community and group sociology. Affective commitment pertains to emotional attachment to a group, community, or organization (Ellemers et al., 1999; Meyer & Allen, 1991). Despite its relatively clear definition, different theories, models, and disciplines name and conceptualize affective commitment differently. Organizational studies tend to use affective commitment as a component of organizational commitment (Meyer & Allen, 1991). Research rooted in social psychology or group sociology views affective commitment as a component of social identity (Bergami & Bagozzi, 2000; Ellemers et al., 1999), a component of sense of community and named sense of belonging (Blanchard & Markus, 2004; McMillan & Chavis, 1986), a component of social capital and named identification (Chiu et al., 2006), and also a distinct construct referred to as attachment (Ren et al., 2012).

Several studies conceptualize affective commitment as one of the three components of organizational commitment (Allen & Meyer, 1990, 1996; Meyer & Allen, 1984, 1991). Accordingly, affective commitment pertains to “identification with, involvement in, and emotional attachment to the organization” (Allen & Meyer, 1990, p. 253). The two other components of organizational commitment are continuance commitment and normative commitment. Continuance commitment reflects “the perceived costs associated with leaving the organization (Meyer, Stanley, Herscovitch, & Topolnytsky, 2002, p. 21); whereas, normative commitment refers to "a feeling of obligation to continue employment” (Meyer & Allen, 1991, p. 67). Since the three-factor model's development, research that focuses on organizational commitment and employee behaviors has extensively used this three-factor model as its basis (e.g., Meyer et al., 2002). Additionally, the proliferation of online communities have recently motivated IS researchers to adopt the organizational commitment model and use it in the context of online communities. This motivation lies partly in the inherent similarities between online communities and traditional organizations in terms of social structure and social behaviors displayed by the members. For instance, Bateman et al. (2011a) extend the three-component model of organizational commitment to online communities. They define three corresponding constructs as continuance community commitment, affective community commitment, and normative community commitment. Accordingly, they define affective community commitment as “a bond between a member and a particular community that is based on the member's strong emotional attachment to that community” (p. 843). They examined the impact of affective community commitment and the two other components of community commitment on user participation in an online community. The results of their study indicated that affective commitment affects user participation in terms of posting replies to others' questions and comments. Moreover, they found that affective commitment had a significant relation with moderating discussions.

Other studies have viewed affective commitment as a component of social identity (e.g., Ellemers et al., 1999; Bergami & Bagozzi, 2000). In the realm of social media, Bagozzi and Dholakia (2002) adopt a social identity perspective to examine the determinants of participation in online communities. They postulate that virtual communities are socially rich environments that enhance the development of community member's social identity. Subsequently, this social identity affects member's participation behaviors in these communities. Bagozzi and Dholakia (2002) conceptualize social identity as a three-component factor including self-categorization, affective commitment, and group-based self-esteem. They argue that affective commitment in this model reflects the emotional component of community membership. The results of this study confirmed that affective commitment, as a component of social identity, is a significant driver for participation in virtual communities.

Sense of belonging, also known as membership, is another construct that is very similar to affective commitment in theoretical and conceptual terms. Researchers conceptualize this construct as a component of a higher-level construct, sense of community, which refers to “a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to be together” (McMillan & Chavis 1986; p. 9). McMillan and Chavis (1986) propose a four-factor model of sense of community comprising membership, influence, integration and fulfillment of needs, and shared emotional connection. In their model, membership denotes the feeling of belonging to a community and is in line with the notion of affective commitment (Zhang, 2010).

Some researchers have applied the four-factor model of sense of community in the context of online communities. Blanchard and Markus (2004) found that the dimensions of sense of community were very similar to those that McMillan and Chavis (1986) suggest. Zhang (2010) confirmed the applicability of this four-factor model in the SNS domain. He also found that sense of community had strong relations with SNS usage and satisfaction. Other studies suggest that sense of belonging can positively affect participation and knowledge contribution intensions and behaviors in online communities. Yoo, Suh, and Lee (2002), for example, demonstrated that sense of belonging positively influenced participation in virtual communities. Teo, Chan, Wei, and Zhang (2003) found that sense of belonging has a significant relation with intention to use virtual learning communities. Chai and Kim (2011) found a significant relation between sense of belonging in SNSs and knowledge contribution in those networks. Zhao, Lu, Wang, Chau, and Zhang (2012) also found that sense of belonging positively affected intention to get knowledge and intention to share knowledge in virtual communities.

Identification is another construct used in the IS literature that refers to the same concept as affective commitment or sense of belonging. Chiu et al. (2006) define identification as “an individual's sense of belonging and positive feeling toward a virtual community” (p. 1877). They draw on social capital theory and argue that identification is a component of relational capital. The results of their study showed that identification had a positive relation with quantity of knowledge shared in online communities. Extant literature has also conceptualized affective commitment as attachment and suggested that member attachment to online communities positively influences participation in the community, which eventually leads to the community growth, success, and sustainability (Preece, 2001). Ren et al. (2012) argue that “the construct attachment overlaps with those of commitment and identification; the three are often used interchangeably” (p. 842). In line with prior studies in social psychology (Prentice, Miller, & Lightdale, 1994), Ren et al. (2012) suggest that the two ways by which community members feel attached to a group are: 1) attachment through group identity (identity-based attachment) and 2) attachment through interpersonal bonds (bond-based attachment). Based on their conceptualization of attachment, Ren et al. (2012) conducted an experimental study in the context of online movie communities and found that both identity-based and bond-based attachments played a role in user participation in those communities. However, identity-based attachment had stronger effects on participation and willingness to help a subgroup in the community. Taken together, the literature has termed and conceptualized affective commitment in different ways; however, researchers have consistently showed this construct to be a significant driver for participation in online communities.

Collectively, prior research in healthcare information systems, social media, health-related online communities, and information privacy has identified several important factors that influence information disclosure in different contexts. However, little research has specifically looked at individuals' perceptions, attitudes, beliefs, and behaviors concerning PHI disclosure and the trade-off between privacy concerns and perceived benefits of this disclosure in the context of VHCs. Additionally, prior research has emphasized the potential impact of affective commitment on user participation in different types of online communities (Bateman et al., 2011a) and, more specifically, in public VHCs discussions (Chung, 2014). Therefore, in this study, we adopt the notion of privacy calculus, incorporate affective commitment into the generic privacy calculus model, and focus on a specific collaboration platform (namely, discussion boards) to investigate PHI sharing intentions in VHCs. In Section 3, we present the hypotheses and research model.

3 Hypotheses and Research Model

People join VHCs to seek and provide informational and emotional social support in communications with other individuals (Owen, Klapow, Roth, Nabell, & Tucker, 2004; Wright & Bell, 2003). To do so, people may engage in self-disclosure behaviors and PHI sharing activities while communicating with others through discussion boards (Barak & Gluck-Ofri, 2007). A potential driver for communicating PHI in these environments is the immediate positive outcomes that this form of PHI revelation can provide for contributors. For instance, people may perceive that, if they talk about their PHI on discussion boards, they will more likely find others with similar health conditions or experiences. As a result, they can make social ties and exchange knowledge on the medical issues of interest or concern to them. Also, one may believe that disclosing more PHI will help community members to better learn about their medical situation, and consequently, provide them with more relevant and useful health-related experiences and advice.

People may believe that communicating PHI on discussion boards may provide a sense of relief for them (Shim, Cappella, & Han, 2011; Van Uden-Kraan et al., 2008), which can be more important for patients suffering from mental conditions such as depression and anxiety (Houston, Cooper, & Ford, 2002). A sense of importance and helpfulness can be another expected positive outcome from communicating PHI and supporting others in the community (Wright & Bell, 2003). In general, we define expected positive personal outcomes of communicating PHI in VHCs as individuals' judging that they will likely benefit from communicating their PHI in public VHC discussions. We expect that the more people believe that communicating PHI can provide benefits for them, the more likely they will engage in personal information sharing behaviors. Thus, we hypothesize:

> **H1:** Expected positive personal outcomes will increase one's willingness to communicate PHI in public VHC discussions.

Prior research demonstrates that providing support and being helpful to community members is a prominent motivation for joining and contributing to online communities (Chiu et al., 2006), which can also apply to VHCs. Individuals participate in discussion topics and talk about their PHI such as experiences of undergoing medical tests and treatments to help other community members with similar health conditions or concerns (Chung, 2011; Evans et al., 2012; Oh, 2012). Moreover, the information shared on discussion boards usually persists as long as the community website exists. Therefore, this information can potentially be accessible and useful for individuals who join the community in the future (Holbrey & Coulson, 2013). Thus, we argue that, if people believe that the PHI they communicate to the community provides helpful outcomes for the community, they will more likely engage in these sharing behaviors. To better conceptualize those outcomes for the community, we define expected community-related outcomes of sharing PHI in VHCs as the extent to which individuals judge that the online community they share their PHI in will benefit from their sharing such information. Thus, we hypothesize:

> **H2:** Expected positive community-related outcomes will increase one's willingness to communicate PHI in public VHC discussions.

Research has shown privacy concern is a major barrier to personal information disclosure in different types of online communities (Bateman, Pike, & Butler, 2011b; Krasnova et al., 2009). Research has also demonstrated that people are less willing to share PHI through traditional healthcare information systems (Anderson & Agarwal, 2011) and online healthcare websites (Bansal, Zahedi, & Gefen, 2010) if they believe this disclosure may threaten their privacy. Thus, sharing PHI in VHCs can also raise privacy concerns for information providers. Individuals are concerned that the PHI that they disclose in VHCs may be collected, used, and disseminated in an unauthorized and unanticipated manner (Williams, 2010).

A main reason for this concern is that, as opposed to other types of SNSs, the nature of participating in VHCs relies primarily on communicating PHI to other members of the community. Moreover, the visibility of information shared on blogs, profile pages, and publicly available discussion forums on VHCs presents high levels of privacy risk that can ultimately make people less inclined toward participating in these online communities (Rossi & Tognetti Bordogna, 2014). In other words, individuals do not control the level of public accessibility to the information revealed through public VHC collaboration platforms. Accordingly, we contextualize privacy concern in the area of VHCs and define it as the extent to which individuals feel concerned about sharing their PHI in public VHC discussions. We believe that PHI privacy concerns may decrease individuals' willingness to share PHI within these virtual environments while communicating with others. Therefore, we hypothesize:

> **H3:** PHI privacy concern will decrease one's willingness to communicate PHI in public VHC discussions.

In the context of virtual communities, affective commitment reflects the emotional bonds between individuals and these communities. As we discuss earlier, the extant literature demonstrates that, from the perspectives of organizational commitment (Bateman et al., 2011a), social identity (Bagozzi & Dholakia, 2002), sense of community (Chai & Kim, 2011; Teo et al., 2003; Zhang, 2010), and social capital theory (Zhao, Lu, Wang, et al., 2012), affective commitment has a significant relation with participation in virtual communities. Moreover, prior studies highlight the emotional aspect of social support (Buis, 2008; Monge & Contractor, 2003) and support exchange activities in VHCs (Evans et al., 2012; Kordzadeh et al., 2014), which can make the role of affective commitment in these online environments more salient. Therefore, we expect that affective commitment drives participation in terms of communicating PHI in VHCs. We believe that individuals who feel a stronger sense of belonging to VHCs will be more willing to disclose PHI in order to contribute to public discussions. Thus, we hypothesize:

H4: Affective commitment will increase one's willingness to communicate PHI in public VHC discussions.

The affect theory of social exchange (Lawler, 2001) postulates that emotion is a central feature of social exchange processes and can shape individuals' feelings about their shared activities, relations, and common affiliations in a community. Accordingly, emotion may impact one's perception of shared responsibility, which can ultimately influence individuals' willingness to sacrifice and invest resources such as time and energy in their interactions with a community's members.

Affective commitment lies in the emotional attachment of individuals to communities (Bateman et al., 2011a; Chai & Kim, 2011). Therefore, in line with the affect theory of social exchange, we believe that individuals emotionally attached to a VHC will be more willing to sacrifice their privacy concern in favor of achieving their shared responsibility in the community. In other words, we expect that the negative relation between privacy concern and willingness to communicate PHI in a VHC are mitigated when people have a high level of affective commitment to that community. This means that privacy concerns make a more significant impact on the willingness to communicate PHI for people with lower levels of affective commitment to a VHC. Thus, we hypothesize:

H5: High affective commitment reduces the impact of PHI privacy concern on willingness to communicate PHI in public VHC discussions.

Affective commitment has its roots in sense of community (Chai & Kim, 2011; Zhang, 2010). Thus, it can intensify the role of community-related factors in individuals' intentions and behaviors in online communities (Bateman et al., 2011a). This is also consistent with the affect theory of social exchange (Lawler, 2001) in that emotionally attached individuals to a community are more likely to care about their shared responsibility in terms of providing social support to other members of that community. Accordingly, in the context of VHCs, we argue that the impact of perceived community-related outcomes on willingness to communicate PHI to VHCs is more significant for the community members with higher levels of affective commitment. Conversely, the PHI sharing intentions of individuals with lower levels of affective commitment are expected to be less influenced by their perceptions of community-related benefits of communicating PHI to the community. Hence, we hypothesize:

H6: High affective commitment increases the impact of community-related outcomes on willingness to communicate PHI in public VHC discussions.

Figure 1 illustrates the research model that depicts Hypotheses 1 through 6.

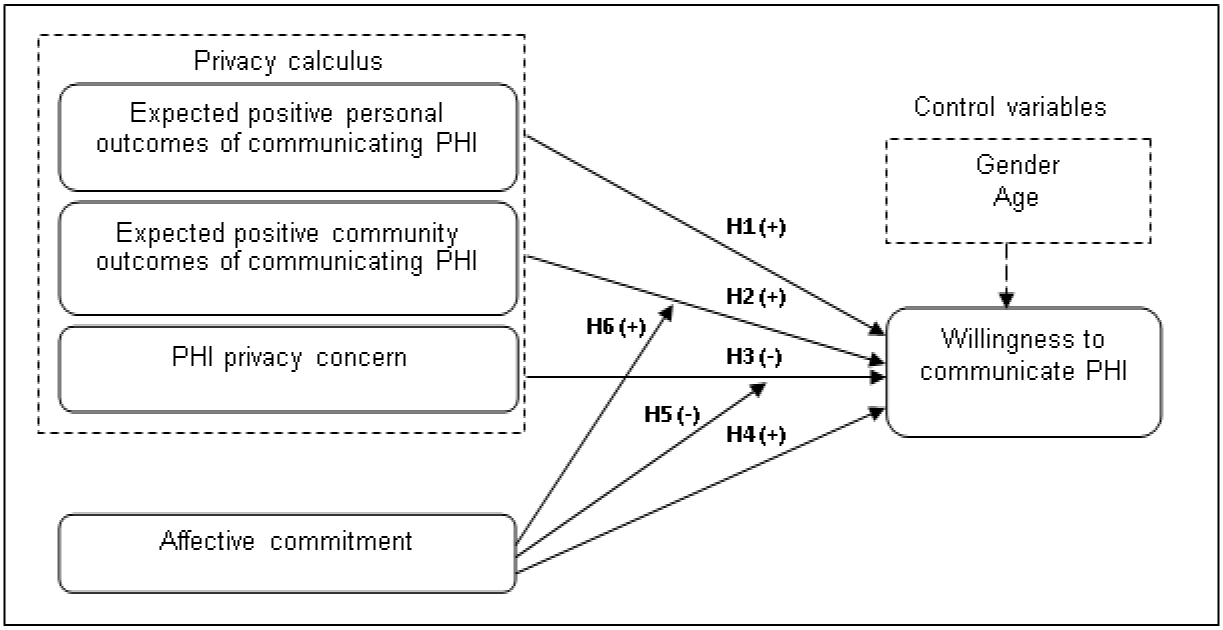

Figure 1. Research Model and Hypotheses

4 Method

4.1 Instrument Development

In order to test the hypotheses, we conducted a survey study. We adopted an initial set of measurement items from the existing literature. We adjusted the items' wording to make them fit into the context of the current research study. Additionally, in order to enhance the validity of the instrument, we reverse-coded some items in different scales. We measured all attitudinal and perceptual items on seven-point Likert scales anchored on "1 = strongly disagree" and "7 = strongly agree". We also included demographic items including age, gender, ethnicity, and education in the instrument. The existing literature often suggests these variables as potential influential factors on information disclosure and privacy perceptions and behaviors. We adopted and made minor changes to the levels of age and education and to the ethnicity types that Anderson and Agarwal (2011) propose.

4.2 Content Validation

We assessed the content validity of the items by holding three focus group sessions. The experts who participated in these sessions included two faculty members and three PhD students in a large public university in the United States. The participants in these sessions had previous experience with behavioral research in the area of information security/privacy or other relevant areas in the information systems discipline. Each session took from one hour and thirty minutes to two hours. During each session, the experts discussed how the measurement items were worded and if the constructs represented the items that they were intended to measure. In addition to these sessions, the experts exchanged numerous emails to further discuss the potential issues and improvement opportunities regarding the scales. Finally, based on the consensus among the experts in these sessions, we removed, revised, and combined several items and, ultimately, approved the content validity of the instrument. Table 1 presents the final set of measurement items along with their original source in the literature and the construct definitions.

4.3 Instrument Organization and Administration

The instrument started with a priming section that explained the primary concepts in the survey and directed the respondents toward the subsequent sections in the survey. The definitions of health information and health-related virtual communities provided in this section to the respondents were as follows:

- Health information: in this study, your health information refers to the information about your diseases, diagnosis, medications, test results, hospital procedures, experiences, feelings about experiences, etc. Please note that this survey will not collect any health information.
- Health-related virtual communities: a health-related virtual community is a website that enables people to create profile pages, post information, and participate in online discussions of health-related information.

We categorized respondents into two groups. Group 1 included the respondents who were members of at least one VHC. We asked these individuals to think of a specific VHC of which they were a member. We then asked them to continue with the survey. Group 2 included individuals who were not members of any VHC; however, they were familiar with the concept of virtual communities. We asked these individuals to imagine that they were going to join a health-related virtual community. We then asked them to continue with the survey after skipping the affective commitment items that we specifically designed for group 1 individuals to answer. We did not include individuals who did not fit group 1 or 2 categories in the study.

We collected data from three different sources including 1) students, 2) faculty and staff, and 3) visitors to a clinic. Following prior studies (e.g., Dinev & Hart, 2006), we used different sources for data collection to increase the sample size and enhance the statistical power of the data analysis and results. Moreover, selecting samples from different sources enhanced the diversity of respondents in terms of perceptions, attitudes, and demographic characteristics. This diversity ultimately improved the external validity and generalizability of the results. The surveys were paper based, and we grouped the measurement items by construct.

Table 1. Theoretical Constructs and Measurement Items

Construct	Reference	Construct definition	Measurement items
Willingness to communicate PHI	Bansal, Zahedi, & Gefen (2010)	The extent to which one is willing to disclose PHI in public discussions within VHCs.	1. I would talk about my health information in public discussions. 2. I would share my health information in public discussions. 3. I would be reluctant to communicate my health information in public discussions.
PHI privacy concern	Xu et al. (2011)	The extent to which individuals feel concerned about sharing their PHI in public VHC discussions.	1. I would talk about my health information in public discussions. 2. I would share my health information in public discussions. 3. I would be reluctant to communicate my health information in public discussions. 4. I am concerned about revealing my health information in public discussions because it could be used in a way I did not foresee.
Expected positive personal outcomes of sharing PHI	Chiu et al. (2006)	Individuals' judging that they will likely benefit from communicating their PHI in public VHC discussions.	1. Sharing my health information in public discussions will help me connect with people who have similar health experiences. 2. Sharing my health information in public discussions is good for my wellbeing. 3. Personal benefits of talking about my health information in public discussions will be trivial. 4. There are advantages to me from communicating my health information in public discussions.
Expected positive community-related outcomes of sharing PHI	Chiu et al. (2006)	The extent to which individuals judge that the online community they share their PHI in will benefit from their sharing such information.	1. Sharing my health information will help other community members. 2. Health information that I communicate will benefit members with similar health conditions. 3. Talking about my health information is worthless for this virtual community. 4. The health information I share is valuable to members of this virtual community.
Affective community commitment	Bateman et al. (2011a)	Identification with, involvement in, and emotional attachment to a VHC.	1. I feel like a part of the group at this virtual community. 2. I have an emotional attachment to this virtual community. 3. This virtual community has personal meaning for me. 4. I feel a sense of belonging to this virtual community. 5. I feel indifferent toward this virtual community.

4.3.1 Students

Researchers have used students as target populations in various observational and experimental studies in the context of online social networks, health websites, and privacy behaviors (Bansal et al., 2010). Moreover, researchers have demonstrated that the younger generation including students are a dominant cohort of the Internet users (Drennan, Sullivan, & Previte, 2006) who use social media platforms for general-purpose social interactions (Xu et al., 2013) and health communications (Chou, Hunt, Beckjord, Moser, & Hesse, 2009). They may visit VHCs to seek and provide social support related to their own medical concerns or their parents', families', or friends' medical questions and issues. Thus, we administered our survey to students in a large public university in the southern area of the United States.

One of the researchers recruited students from those who had enrolled in any of the four sections of an introductory information systems course in the fall of 2013. The researcher attended each class and briefly explained the intent of the research and the process of the survey administration. The students could opt-out of the study if they wished. In total, we collected 146 usable surveys from the respondents, of which 72 individuals were actual members of at least one VHC (group 1), and 74 individuals were familiar but not members of any VHCs (group 2).

4.3.2 Faculty and Staff

Individuals in this group may visit VHCs to seek information regarding their medical concerns and to provide support for other individuals in these communities. We selected a convenience sample of 60 individuals from faculty and staff in the same university used for collecting data from students. One of the researchers stopped by the subjects' offices, introduced himself, and briefly explained the purpose and procedure of this study. He gave each subject a copy of the consent form and the actual survey and an envelope with the researcher's address on it such that the subject could put the completed survey in the envelop and send it anonymously to the researcher. From the 60 individuals, we received 42 completed surveys within a few weeks after giving out the surveys. Among the 42 subjects who returned the completed surveys, 11 respondents were actual members of VHCs (group 1) and nine individuals were only familiar with VHCs (group 2).

4.3.3 Visitors to Clinics

We collected data from the visitors to the clinics over a five-week period in 2014. During this period, the researcher attended the clinics on a daily basis, approached the patients and their families in the waiting room, introduced himself and the study, and asked if they would be willing to participate in this survey study. He provided a paper survey to those who agreed to participate in the study. In total, we collected 69 completed surveys: 42 individuals were in group 1 (actual members of VHCs) and 27 individuals were in group 2 (familiar with VHCs). Table 2 summarizes the sampling.

Table 2. A Summary of Sampling

	Group 1	Group 2	Subtotal
Students	74	72	146
Faculty/Staff	11	9	20
Clinic Visitors	42	27	69
Subtotal	127	108	235

5 Data Analysis and Results

5.1 Demographics

In order to test the hypotheses, we consolidated the data collected from students, faculty and staff, and visitors to the clinics. Table 3 summarizes the demographic information corresponding to the subjects of groups 1 and 2 in the final dataset. Accordingly, 51.2 and 50.0 percent of the subjects of groups 1 and 2 were female, respectively. Thus, given that the subjects with missing values on gender constituted less than 5 percent of the entire subjects, the gender distribution was adequately balanced. With regard to age, almost half of the subjects were from the age range of 18 to 24. A majority of the remaining subjects were aged between 25 to 54 years old. In addition, approximately 20 percent of the group 1 and 2 subjects were greater than 44 years old. Further, 70 percent of the subjects of groups 1 and 2 were either White or Hispanic. We expected this result since we selected the subjects from a southern area in the United States and the two dominant races/ethnicities in that area include White and Hispanic people.

Table 3. Demographic Characteristics of the Sample (Full Dataset)

	*Group 1	**Group 2	***Total
N	127	108	235
Gender			
Female	65 (51.2%)	54 (50.0%)	119 (50.6%)
Male	57 (44.9%)	49 (45.4%)	106 (45.1%)
Missing	5 (3.9%)	5 (4.6%)	10 (4.3%)
Age			
18 – 24	58 (45.7%)	58 (53.7%)	116 (49.3%)
25 – 34	29 (22.8%)	21 (19.4%)	50 (21.3%)
35 – 44	15 (11.8%)	8 (7.4%)	23 (9.8%)
45 – 54	13 (10.2%)	5 (4.6%)	18 (7.7%)
55 – 64	6 (4.7%)	10 (9.3%)	16 (6.8%)
65 – 74	1 (0.8%)	1 (0.9%)	2 (0.9%)
> 74	1 (0.8%)	1 (0.9%)	2 (0.9%)
Missing	4 (3.1%)	4 (3.7%)	8 (3.4%)
Ethnicity/race			
White	38 (29.9%)	43 (39.8%)	81 (34.5%)
American Indian or Alaska Native	2 (1.6%)	0 (0.0%)	2 (0.9%)
Asian	9 (7.1%)	6 (5.6%)	15 (6.4%)
African American	6 (4.7%)	10 (9.3%)	16 (6.8%)
Hispanic	52 (40.9%)	41 (38.0%)	93 (39.6%)
Native Hawaiian or Other Pacific Islander	0 (0.0%)	0 (0.0%)	0 (0.00%)
Others	16 (12.6%)	4 (3.7%)	20 (8.5%)
Missing	4 (3.1%)	4 (3.7%)	8 (3.4%)

Note: *Values in parentheses: percentage of the group 1 subjects
**Values in parentheses: percentage of the group 2 subjects
***Values in parentheses: percentage of the group 1 and group 2 subjects, combined.

5.2 Measurement Validity and Reliability

After consolidating the data collected from different sources and examining the demographic characteristics of the subjects, we used SPSS 22.0 to conduct two sets of principal component analysis (PCA) with Promax rotation on the data collected from group 1 and on the data collected from group 2 subjects. In each of the two sets of analysis, we performed PCA, excluded the items that loaded significantly on more than one factor or did not load significantly on any factor, and then re-performed PCA on the remaining items. Although researchers do not agree regarding a cut-off point for a factor loading value to be considered high or low, one of the common cut-off values for assessing cross-loadings is 0.3 (e.g., Hair, Anderson, & Tatham, 1987; Tabachnick & Fidell, 2001). This cut-off suggests that items with loadings greater than 0.3 on more than one factor are, in fact, highly correlated with at least two factors; hence, one needs to remove those items from the final factor structure. Following this rule, we used a 0.3 threshold for assessing cross-loadings and decided on keeping or removing items from the factor structure in each round of PCA accordingly.

Tables 4 and 5 present the final results of the two sets of PCA on group 1 and group 2 subjects, respectively. Accordingly, the final factor structures are consistent. The results of the first PCA revealed that 84 percent of the variation in the 14 items was explained with the five factors extracted. The factor loadings table (Table 4) shows that, at the end of this set of analysis, all items loaded significantly on their intended constructs (> 0.618). The cross-loadings were all less than the 0.3 threshold with the exception of PO1 with a cross-loading of 0.307. Nevertheless, considering that this value (0.307) is marginally greater than 0.3 and that this item loaded significantly on its focal construct, we decided to keep the item in the scale.

Table 4. Factor Loadings (Group 1 Subjects)

	Component				
	1	**2**	**3**	**4**	**5**
WC1	.062	-.116	.039	.041	**.976**
WC2	-.068	.130	-.024	-.064	**.949**
AC1	**.793**	.195	.004	-.118	.008
AC2	**.946**	-.178	-.005	-.090	-.011
AC3	**.845**	-.057	-.032	.127	.074
AC4	**.908**	.096	.032	.074	-.065
PC1	.001	.004	**.917**	-.047	-.006
PC3	.004	.021	**.952**	.002	-.011
PC4	-.006	-.038	**.946**	.025	.035
PO1	-.043	.307	.056	**.618**	.080
PO2	.027	-.017	-.063	**.778**	.145
PO4	-.026	-.023	.000	**.956**	-.115
CO1	-.077	**.973**	-.015	-.046	-.015
CO2	.043	**.866**	.044	.150	-.092
CO4	.069	**.892**	-.046	-.093	.090

In the second set of PCA, we eliminated the items that measure affective commitment and performed the PCA using the group 2 subjects. Table 5 presents the loadings and cross loading values of the final factor structure. Consistent with the findings of the previous PCA (Table 4), the results (Table 5) showed that all items loaded significantly (> 0.655) on a common factor, whereas the cross-loadings were all less than the 0.3 threshold.

Table 5. Factor Loadings (Group 2 Subjects)

	Component(factor)			
	1	**2**	**3**	**4**
WC1	-.008	.079	**.994**	.014
WC2	-.030	-.050	**.951**	-.005
PC1	.105	**.963**	.296	-.261
PC3	-.096	**.888**	-.125	.172
PC4	-.015	**.834**	-.233	.143
PO1	.021	.032	.047	**.914**
PO2	.082	-.063	.220	**.655**
PO4	.211	-.036	.253	**.727**
CO1	**.860**	.010	.119	-.003
CO2	**.978**	.022	.004	-.068
CO4	**.979**	-.019	-.140	.089

Tables 6 and 7 present the descriptive statistics of the constructs along with the inter-construct correlations for the data collected from group 1 and group 2, respectively. The off-diagonal items in the correlation matrices in both tables display the Pearson correlation coefficients between corresponding latent constructs. The diagonal items list the square root of average variance extracted (AVE) for the corresponding constructs. AVE is used to test the constructs for convergent and discriminant validity. For the purpose of convergent validity assessment, one should examine AVEs to assure that they exceed the threshold of 0.50 (Fornell & Larcker, 1981; MacKenzie, Podsakoff, & Podsakoff, 2011), which shows that the focal construct explains at least 50 percent of the variance in the items (Fornell & Larcker, 1981; Xu, Boh, & Soh, 2014). Moreover, discriminant validity is assured if the square root of AVE for each construct exceeds the correlations between that construct and all other conceptually similar constructs in the study (MacKenzie et al., 2011). As Tables 6 and 7 show, all the constructs met the conditions mentioned above for AVEs. This finding indicates that convergent and discriminant validity was assured and our measures were psychometrically adequate.

Table 6. Inter-Construct Correlations and AVEs (Group 1 Subjects)

Construct	Mean	S.D.	Cronbach's alpha (α)	AVE	1	2	3	4	5
1. Willingness to share	3.49	1.65	0.90	0.925	0.962				
2. Privacy concern	4.30	1.65	0.93	0.880	- 0.262**	0.938			
3. Personal outcomes	4.16	1.38	0.83	0.637	0.736**	- 0.165	0.796		
4. Community outcomes	4.45	1.40	0.91	0.830	0.456**	- 0.016	0.707**	0.911	
5. Affective commitment	3.18	1.43	0.90	0.766	0.336**	- 0.064	0.427**	0.381**	0.875

Note: The diagonal values show the square root of AVE.
*p < 0.05, **p < 0.01

Table 7. Inter-Construct Correlations and AVEs (Groups 2 Subjects)

Construct	Mean	S.D.	Cronbach's alpha (α)	AVE	1	2	3	4
1. Willingness to share	4.17	1.71	0.96	0.946	0.980			
2. Privacy concern	4.69	1.53	0.89	0.804	-0.308**	0.897		
3. Personal outcomes	4.73	1.33	0.87	0.598	0.710**	-0.500**	0.773	
4. Community outcomes	4.98	1.33	0.93	.885	0.610**	-0.291**	0.613**	0.941

Note: The diagonal values show the square root of AVE.
*p < 0.05, **p < 0.01

The correlation coefficients displayed an adequately consistent behavior across the two tables and their corresponding samples. The only difference between the two sets of correlation coefficients was that group 1 subjects' privacy concern did not show a significant correlation with their expected personal and community-related outcomes or affective commitment. Nonetheless, their privacy concern was significantly correlated with their willingness to share PHI. Other than that, we found that all the bivariate correlations between the constructs for group 1 and group 2 subjects were significant.

We also assessed the reliability of the measures using Cronbach's alpha coefficients. Tables 6 and 7 present the results of the reliability measurement for the two groups of subjects. The results showed that Cronbach's alpha coefficients for all the subscales were greater than the suggested threshold of 0.7 (Nunnally, 1978), which demonstrates that the subscales were adequately reliable.

Finally, we addressed the potential issue of common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Straub, Boudreau, & Gefen, 2004). In the survey administration process, we did not provide any incentives to the respondents; rather, we provided enough information to them to assure them that the surveys were anonymous and that there was no single correct answer to any of the questions on the questionnaire. However, we asked the respondents to answer the questions as honestly as possible. In this way, we reduced the threat of social desirability bias or respondent acquiescence (Podsakoff et al., 2003). To further address common method bias, we conducted Harman's single-factor test by loading all items on one factor to "determine whether the majority of the variance can be accounted for by one general factor" (Podsakoff et al., 2003, p. 890). The results revealed that five distinct factors accounted for 84 percent of the variance and the first (largest) factor extracted 41 percent of the variance, which suggests that no general factor could explain the majority (> 50%) of variance. Thus, common method bias might not be a major issue in the data.

5.3 Hypotheses Testing

In order to test the hypotheses, we performed two hierarchical moderated multiple regressions (MMR) on the dataset. Research has demonstrated this type of multiple regression method to be an effective statistical analysis to test the models that include interaction effects and main effects (Carte & Russell, 2003; Saunders, 1956).

5.3.1 A-Priori Power Analysis

Before conducting the MMR models and to ensure that the sample size in each group was adequate for running the regression models, we ran a set of a-priori power analysis using G*Power 3.1 at different levels of power (i.e., from 0.7 to 0.9). The results showed that the largest minimum required sample size for groups 1 and 2 were 108 and 99, respectively; whereas, our samples contained 116 and 103 usable data points for groups 1 and 2, respectively. In other words, our sample size for each group was greater than the associated minimum sample size required for conducting regression analysis.

5.3.2 Regression Results

Table 8 presents the results of performing the two MMR models, which we discuss in this section.

Table 8. Results of Regression Analysis (Group 1 vs. Group 2)

	Group 1 subjects			**Group 2 subjects**	
Model	1a	1b	1c	2a	2b
Control variables					
Age	0.065 (0.492)	-0.003 (0.960)	-0.003 (0.963)	0.256* (0.027)	0.052 (0.459)
Gender	0.073 (0.441)	-.018 (0.785)	- 0.014 (0.837)	-0.631 (0.058)	-0.406* (0.042)
Main effects					
Personal outcomes (PO)		0.553*** (0.000)	0.550*** (0.000)		0.681*** (0.000)
Community outcomes (CO)		0.190* (0.036)	0.189* (0.041)		0.285* (0.013)
Privacy concern (PC)		-0.253*** (0.000)	-0.264*** (0.000)		-0.199** (0.007)
Affective commitment (AC)		0.005 (0.936)	0.020 (0.779)		
Interaction effects					
Affective commitment × privacy concern			-0.046 (0.499)		
Affective commitment × community outcomes			0.006 (0.925)		
R^2	0.011	0.595	0.597	0.077	0.684
Adjusted R^2	**-0.006**	**0.573**	**0.567**	**0.058**	**0.668**
ΔR^2	0.011	0.584	0.002	0.077	0.607
ΔF	0.649	39.294***	0.230	4.157*	62.171***
	N = 116; values of predictors are mean-centered.			N = 103	
Notes: values in parentheses are p values. *p < 0.05, **p < 0.01, ***p < 0.001.					

Results for group 1 subjects: using the data collected from the group 1 subjects, we ran the first model (Equation 1).

$$WC = \beta_0 + \beta_1 AGE + \beta_2 GENDER + \beta_3 PO + \beta_4 CO + \beta_5 PC + \beta_6 AC + \beta_7 AC.PC + \beta_8 AC.CO + \varepsilon, \qquad (1)$$

where:

WC = willingness to communicate PHI

PO = personal outcomes of communicating PHI

CO = community-related outcomes of communicating PHI

PC = privacy concern, and

AC = affective commitment.

Willingness to communicate PHI is the dependent variable (DV) in this model. Personal outcomes, community-related outcomes, privacy concern, and affective commitment, (β3 – β6) and the interaction terms between affective commitment and the two predictors including privacy concern and community-relate outcomes (β7 and β8) constitute the independent variables (IVs). Age and gender (β1 and β2) are also the control variables in the model. However, we entered the variables into the model in a hierarchical procedure such that we ran the model three times with three different sets of predictors. First, we only included the control variables on the predictors' side (column 1a). The results did not show any significant relation between neither of the control variables and the DV. The adjusted R^2 was -0.006, which indicates that age and gender did not explain a significantly high proportion of the variation in the DV.

In the second run of the regression analysis, we entered the four IVs into the model. According to the results (column 1b), the adjusted R2 increased to 0.573 and the ΔF was significant (ΔF = 39.294, $p < 0.001$). These results suggest that adding the IVs significantly improved the explanatory value of the model. Furthermore, the beta coefficients of the IVs showed that personal outcomes (β = 0.553, $p < 0.001$), community-related outcomes (β = 0.190, $p < 0.05$), and privacy concern (β = - 0.253, $p < 0.001$) significantly impacted willingness to communicate PHI. Nonetheless, we detected no significant relation between affective commitment and the DV. These results support H1, H2, and H3 but do not support H4. Accordingly, people with greater expected personal outcomes (H1) and community-related outcomes (H2) and/or with lower privacy concern (H3) are more willing to communicate PHI in public VHC discussions. However, people with different levels of affective commitment may or may not be willing to communicate PHI in VHC discussions. Neither of the control variables showed a significant relation with the DV in this model.

Finally, in order to test the moderating effects of affective commitment associated with H5 and H6, we entered the interaction terms into the model (column 1c). We calculated these interaction terms manually in SPSS by multiplying the mean-centered values of affective commitment by the mean-centered values of privacy concern and community-related outcomes in two separate columns. We used mean-centered values as opposed to raw values of the predictors in the regression model to resolve potential multi-collinearity issues in the data and improve interpretability of the results (Aiken, West, & Reno, 1991). The adjusted R^2 of this model was 0.567, which suggests that adding the interaction terms into the model did not significantly improve the explanatory value of the model ($\Delta R^2 = 0.002$ and ΔF = 0.230). The results, however, reconfirmed the significant relations between personal outcomes (β = 0.550, $p < 0.001$), community-related outcomes (β = 0.189, $p < 0.05$) and privacy concern (β = - 0.264, $p < 0.001$) with willingness to communicate PHI. Nevertheless, affective commitment (β = 0.020, $p > 0.05$) again did not show a significant relation with willingness to communicate PHI. Thus, the results do not support H4, which posits that individuals with higher affective commitment to a VHC are more willing to communicate PHI in public discussions in that VHC.

The differences in the F-values and R^2 of the model, with and without interaction terms, were not significant. This result indicates that the moderating effects in the model were not supported (Carte & Russell, 2003). However, we also probed the beta coefficients of the interaction terms to further analyze the moderating effects proposed in the theoretical model. The interaction term between affective commitment and privacy concern (β = - 0.046, p = 0.499) did not show a significant relation with the DV in the model. As such, this result does not support H5, which posits that higher affective commitment relaxes the negative relation between privacy concern and willingness to communicate PHI. Furthermore, the interaction term between affective commitment and community-related outcomes (β = 0.006, p = 0.925) was not statistically significant. This finding does not support H6, which posits that higher affective commitment intensifies the relation between community outcomes and willingness to communicate PHI.

Results for groups 2 subjects*:* in the second MMR model (Equation 2), we used only the data collected from the subjects of group 2. We did so to investigate any potential differences in the results when considering the subjects who were actual members of VHCs compared with the results associated with those who were merely familiar with those online communities. Moreover, because group 1 subjects were the only individuals who responded to the affective commitment items, we eliminated affective commitment and the interaction terms in this model.

$$WC = \beta_0 + \beta_1 AGE + \beta_2 GENDER + \beta_3 PO + \beta_4 CO + \beta_5 PC + \varepsilon, \qquad (2)$$

where:

WC = willingness to communicate PHI

PO = personal outcomes of communicating PHI

CO = community-related outcomes of communicating PHI, and

PC = privacy concern.

Similar to the hierarchical procedure that we employed to run the first MMR model, we entered the variables in the second MMR in a step-wise manner. Thus, the control variables (age and gender) were the only predictors we entered into the first block of the model. The results presented in column 2a of Table 8 show that age positively influenced willingness to communicate PHI ($\beta = 0.256$, $p < 0.05$) and that we detected no significant relation between gender and the DV. The adjusted R^2 was 0.058.

Next, we added the three IVs into the model (block 2) and re-ran it. The results (column 2b) demonstrated that personal outcomes ($\beta = 0.681$, $p < 0.001$) and community-related outcomes ($\beta = 0.285$, $p < 0.05$) showed significant relations with the DV, which again supports H1 and H2. In addition, the results demonstrated a negative relation between privacy concern ($\beta = -0.199$, $p < 0.01$) and willingness to communicate PHI. This finding also supports H3. The adjusted R^2 of this model was 0.668 and $\Delta F = 62.171$ ($P < 0.001$), which suggests that adding the three IVs into the model significantly improved its explanatory power.

In the process of running the regression models (Equations 1 and 2), we investigated the observations to detect potential outliers using Cook's distance statistic (Cook, 1977). Using the cutoff point of 4/n for Cook's distance, where n is the number of observations (Bollen & Jackman, 1985), we eliminated 11 cases from the initial 127 cases in group 1 and five cases from the initial 108 cases in group 2 from the dataset. Consequently, we used 116 and 103 cases from groups 1 and 2, respectively, to perform the final MMR models. We also conducted collinearity diagnostics while performing regression models. The results revealed that the maximum variance inflation factors (VIFs) in the models associated with Equations 1 and 2 were 2.407 and 2.547, respectively, which were both less than the cut-off value of 10 (Myers, 1990). Thus, multi-collinearity was not an issue in any of the models.

5.4 Post hoc Analysis

Our sample included both members (group 1) and non-members (group 2) of VHCs. Additionally, students constituted the majority of the sample in both groups. Therefore, to understand the potential differences between students and non-students and also between group 1 and group 2 subjects in terms of the privacy calculus factors (namely, willingness to share PHI, PHI privacy concern, personal outcomes of sharing PHI, and community-related outcomes of sharing PHI), we conducted three sets of analysis of variance (ANOVA). We also did so to rule out any confounding effects of studentship on our results.

5.4.1 ANOVA #1: Group 1 vs. Group 2 subjects

In the first set of ANOVA, we compared group 1 and group 2 subjects. The results in Tables 9 and 10 showed that the mean value of all the factors except privacy concern were significantly different between group 1 and group 2 subjects. In particular, non-members were more willing to share their PHI because, perhaps, they expected to receive and provide greater personal and community-related outcomes by sharing their PHI in online discussions.

Table 9. ANOVA Results: Group 1 vs. Group 2

Variable		Sum of squares	df	Mean square	F	Sig
WC	Between groups	22.665	1	22.665	8.042	.005
	Within groups	611.588	217	2.818		
	Total	634.253	218			
PC	Between groups	8.318	1	8.318	3.286	.071
	Within groups	549.254	217	2.531		
	Total	557.572	218			
PO	Between groups	18.319	1	18.319	9.978	.002
	Within groups	398.398	217	1.836		
	Total	416.716	218			
CO	Between groups	14.943	1	14.943	7.962	.005
	Within groups	407.265	217	1.877		
	Total	422.208	218			

Table 10. Mean Values and Standard Deviations: Group 1 vs. Group 2

	WC	PC	PO	CO
Group 2: non-members (N = 103)	4.17 (1.71)	4.69 (1.53)	4.73 (1.33)	4.98 (1.33)
Group 1: members (N = 116)	3.49 (1.65)	4.30 (1.65)	4.16 (1.38)	4.45 (1.40)

5.4.2 ANOVA #2: Students vs. Non-students

To test whether students and non-students differed with regard to the privacy calculus factors, we ran the second set of ANOVA. The results suggested that students were also different from non-students in terms of all the factors except privacy concern. More specifically, students were, overall, less willing to share their PHI in online discussions possibly because, according to our findings, their expected personal and community-related outcomes were significantly less than those of non-students. Tables 11 and 12 provide the results.

Table 11. ANOVA Results: Students vs. Non-students

		Sum of squares	df	Mean square	F	Sig
WC	Between groups	29.014	1	29.014	10.402	.001
	Within groups	605.240	217	2.789		
	Total	634.253	218			
PC	Between groups	7.877	1	7.877	3.110	.079
	Within groups	549.695	217	2.533		
	Total	557.572	218			

Table 11. ANOVA Results: Students vs. Non-students

PO	Between groups	30.499	1	30.499	17.136	.000
	Within groups	386.218	217	1.780		
	Total	416.716	218			
CO	Between groups	21.701	1	21.701	11.758	.001
	Within groups	400.507	217	1.846		
	Total	422.208	218			

Table 12. Mean Values and Standard Deviations: Students vs. Non-students

	WC	PC	PO	CO
Non-students (N = 84)	4.26 (1.72)	4.24 (1.57)	4.90 (1.33)	5.10 (1.28)
Students (N = 135)	3.51 (1.63)	4.63 (1.60)	4.13 (1.34)	4.45 (1.40)

5.4.3 ANOVA #3: 2x2 Factorial Model

We also created a 2x2 factorial model to compare the mean values of the factors across the four possible combinations of the subject groups (group 1 vs. group 2) and studentship (non-student vs. student). The results (see Tables 13 and 14) demonstrated that the actual mean values of the factors were different across the four combinations. Accordingly, non-students of group 2 (non-members) had the highest expected personal and community-related outcomes and the highest willingness to share PHI in online discussions, whereas students of group 1 (members) had the lowest mean values of those factors. Moreover, students who were not members of any VHCs were most concerned about their PHI in those environments, whereas non-students of the same group (non-members) were least concerned about that.

Table 13. ANOVA Results: 2x2 Design

		Sum of squares	DF	Mean Square	F	Sig
WC	Between groups	57.388	3	19.129	7.130	.000
	Within groups	576.866	215	2.683		
	Total	634.253	218			
PC	Between groups	22.034	3	7.345	2.949	.034
	Within groups	535.538	215	2.491		
	Total	557.572	218			
PO	Between groups	56.443	3	18.814	11.228	.000
	Within groups	360.274	215	1.676		
	Total	416.716	218			
CO	Between groups	41.244	3	13.748	7.759	.000

Table 13. ANOVA Results: 2x2 Design

	Within groups	380.964	215	1.772		
	Total	422.208	218			

Table 14. Mean Values and Standard Deviations: 2x2 Design

	WC	**PC**	**PO**	**CO**
Non-member non-students (N = 35)	4.57 (1.76)	4.18 (1.61)	5.10 (1.32)	5.32 (1.30)
Non-member students (N = 68)	3.91 (1.65)	4.95 (1.42)	4.55 (1.30)	4.80 (1.32)
Member non-students (N = 49)	4.03 (1.67)	4.29 (1.56)	4.76 (1.33)	4.94 (1.26)
Member students (N = 67)	3.10 (1.53)	4.31 (1.72)	3.71 (1.25)	4.10 (1.40)

Overall, the results of the ANOVA models revealed that studentship may play a role in determining willingness to share PHI in VHC discussions. Thus, to control for the potential impact of studentship on the results of the regression models, we included a dummy variable representing students vs. non-students in those models and re-ran the analyses. The results (see Table 15) show that, in presence of other predictors in the models, studentship did not significantly impact willingness to share PHI in VHCs. Other findings of these models are consistent with the findings of their corresponding regression models (Table 8). Thus, the results reconfirm the original results of the regression analyses and studentship might not have any adverse effects on the results.

Table 15. Results of Follow-up Regression Analysis in Presence of Studentship (Group 1 vs. Group 2)

	Group 1 subjects			**Group 2 subjects**	
Model	1a	1b	1c	2a	2b
Control variables					
Age	-0.119 (0.281)	-0.022 (0.774)	-0.020 (0.793)	0.134 (0.277)	0.044 (0.551)
Gender	-0.002 (0.982)	-0.006 (0.927)	- 0.001 (0.992)	-0.216* (0.034)	-0.119 (0.053)
Studentship (Student = “1”, non-student = “0”)	-0.348** (0.003)	-0.032 (0.703)	-0.030 (0.723)	-0.138 (0.280)	0.000 (0.999)
Main effects					
Personal Outcomes (PO)		0.544*** (0.000)	0.547*** (0.000)		0.528*** (0.000)
Community Outcomes (CO)		0.187* (0.042)	0.188* (0.044)		0.222* (0.013)
Privacy Concern (PC)		-0.257*** (0.000)	-0.287*** (0.000)		-0.177** (0.008)
Affective Commitment (AC)		0.001 (0.994)	0.018 (0.690)		

Table 15. Results of Follow-up Regression Analysis in Presence of Studentship (Group 1 vs. Group 2)

Interaction Effects					
Affective Commitment × Privacy Concern			-0.059 (0.418)		
Affective Commitment × Community Outcomes			0.018 (0.819)		
R^2	0.088	0.595	0.598	0.088	0.684
Adjusted R^2	**0.064**	**0.569**	**0.564**	**0.060**	**0.664**
ΔR^2	0.088	0.507	0.003	0.088	0.597
ΔF	3.614*	33.846***	0.372	3.169*	60.429***
	N = 116; values of predictors are mean-centered.			N = 103	
Notes: values in parentheses are p values. *p < 0.05, **p < 0.01, ***p < 0.001					

5.5 Summary of Results

In summary, we found support for three of the six hypotheses (H1-H3) we propose in this study. These three hypotheses corresponded to the main effects of personal outcomes, community-related outcomes, and privacy concern on willingness to communicate PHI. However, we did not find support for one of the main effect hypotheses (H4) and the two moderating effect hypotheses (H4 and H5). Table 16 summarizes the results.

Table 16. Summary of the Hypothesis Testing Results

Hypothesis	**Relation**	**Results**	
		Group 1 subjects	Groups 2 subjects
H1: Expected positive personal outcomes will increase one's willingness to communicate PHI in public VHC discussions.	PO → WC	Supported	Supported
H2: Expected positive community-related outcomes will increase one's willingness to communicate PHI in public VHC discussions.	CO → WC	Supported	Supported
H3: PHI privacy concern will decrease one's willingness to communicate PHI in public VHC discussions.	PC → WC	Supported	Supported
H4: Affective commitment will increase one's willingness to communicate PHI in public VHC discussions.	AC → WC	Not supported	-
H5: High affective commitment will reduce the impact of PHI privacy concern on willingness to communicate PHI in public VHC discussions.	AC × PC → WC	Not supported	-
H6: High affective commitment will increase the impact of community-related outcomes on willingness to communicate PHI in public VHC discussions.	AC × CO → WC	Not supported	-

6 Discussion

In this study, we examined various factors that could potentially account for willingness to communicate PHI in public VHC discussions. In particular, we investigated how the both sides of privacy calculus model (expected outcomes and privacy concern of sharing PHI) and affective commitment to VHCs may affect individuals' willingness to share PHI while communicating with others on these virtual platforms. The results associated with the privacy calculus portion of the research model supported the simultaneous impacts of drivers (expected personal and community-related outcomes) and barriers (privacy concern) of communicating PHI in VHCs on the intentions of sharing this information in virtual environments. These results are consistent with the extant literature that has demonstrated the explanatory power of the privacy calculus model in various areas including e-commerce (Dinev & Hart, 2006; Dinev et al. 2006), location-based services (Xu et al., 2009), and general-purpose online social networks (Krasnova & Veltri, 2010).

The results corresponding to the direct and moderating effects of affective commitment, however, did not support the role of this factor in the context of VHCs. These results imply that, regardless of how and to what extent users of VHCs are emotionally attached to these communities, their intentions to share PHI are still primarily accounted for by their expected outcomes (positive) and privacy concerns and not by their affective commitment toward these communities. In addition, the results imply that affective commitment may not significantly relax the impact of privacy concern or intensify the impact of community-related outcomes on PHI sharing in public VHC discussions. Nonetheless, the non-significant results associated with affective commitment might be partially due to the relative skewness of the subjects' responses on the affective commitment items toward lower levels of this construct (mean = 3.18). Further, this construct may impact PHI sharing in online environments through other mechanisms. For instance, it may directly affect privacy concern or perceived benefits of PHI disclosure rather than moderating the relations associated with privacy calculus model. Future studies could examine those potential mechanisms.

Another plausible explanation for this non-significant relationship is that, because affective commitment was significantly correlated with personal and community-related outcomes (Tables 6 and 7), the presence of those two factors in the models captured the impact of affective commitment on the DV. We tested this plausible explanation by adding a middle stage to the hierarchical model by entering affective commitment and privacy concern into the model before entering personal and community-related outcomes. The results of the four-stage MMR model (See Table 17) support the plausible explanation of non-significant relationship between affective commitment and willingness to share PHI. Thus, one can conclude that the correlations between affective commitment and the two expected outcomes factors were high enough to capture the hypothesized impact of affective commitment on willingness to share PHI; nevertheless, those correlations were not that high to introduce multi-collinearity issues in the models.

Table 17. Results of a Four-stage Regression Analysis (Group 1)

	Group 1 subjects			
Model	2a	2b-1	2b-2	2c
Control variables				
Age	-0.119 (0.281)	-0.082 (0.420)	-0.022 (0.774)	-0.020 (0.793)
Gender	-0.002 (0.982)	0.067 (0.442)	-0.006 (0.927)	- 0.001 (0.992)
Studentship (student = "1", non-student = "0")	-0.348** (0.003)	-0.245* (0.024)	-0.032 (0.703)	-0.030 (0.723)
Main effects				
Personal outcomes (PO)			0.544*** (0.000)	0.547*** (0.000)
Community outcomes (CO)			0.187* (0.042)	0.188* (0.044)
Privacy concern (PC)		-0.350*** (0.000)	-0.257*** (0.000)	-0.287*** (0.000)

Table 17. Results of a Four-stage Regression Analysis (Group 1)

Affective commitment (AC)		0.234** (0.008)	0.001 (0.994)	0.018 (0.690)
Interaction effects				
Affective commitment × privacy concern				-0.059 (0.418)
Affective commitment × community outcomes				0.018 (0.819)
R^2	0.088	0.262	0.595	0.598
Adjusted R^2	**0.064**	**0.228**	**0.569**	**0.564**
ΔR^2	0.088	0.174	0.333	0.003
ΔF	3.614*	12.951***	44.498***	0.372
	N = 116; values of predictors are mean-centered.			
Notes: values in parentheses are p values. *p < 0.05, **p < 0.01, ***p < 0.001				

Another interesting finding of this study is that the results of the ANOVA on group 1 versus group 2 subjects revealed that mean values of all constructs except privacy concern differed for groups 1 and 2. The greater positive outcomes of sharing PHI in VHCs that non-members compared with members expect to receive (i.e., personal outcomes) and provide (i.e., community-related outcomes) implies that those individuals may overestimate the benefits of PHI-exchange activities in VHCs because, perhaps, they do not have a realistic understanding of health communications via VHC channels. An implication of this finding is that researchers who study individuals' perceptions and behaviors related to using VHCs should consider these perceptual differences between members and non-members if they want to collect data from non-members or conduct controlled experiments with individuals who are not real members of health social media websites. Moreover, the statistically insignificant difference between mean values of privacy concerns associated with group 1 and group 2 individuals implies that individuals' privacy concerns may be shaped not only by their actual use of those websites but also by other factors such as personality traits (e.g., openness, extraversion, etc.), socio-demographic attributes (e.g., age, gender, etc.), prior experience in information-intensive contexts, or general awareness about privacy risks of sharing personal information in online or offline environments.

The results of the ANOVA on students versus non-students (Tables 11 and 12) suggested that sharing PHI was significantly different between those two groups, although, in the presence of other variables in the regression models, those differences became insignificant. Nonetheless, the potential differences related to information disclosure behaviors of students versus non-students imply that researchers who use students as the only group of subjects in their studies on VHCs should beware that their results may or may not hold if they use non-student subjects. Thus, we suggest that they either use different samples in terms of studentship or be cautious in generalizing their results to different types of individuals.

6.1 Theoretical Implications

Prior studies have demonstrated the validity and robustness of the privacy calculus model in explaining information-sharing intentions and behaviors across various contexts from e-commerce to online social networks. Our findings extend the applications of this model by demonstrating that the components of the model explain a significant percentage of variations in individuals' intentions and behaviors related to sharing PHI in online health-related discussions. Furthermore, few studies related to online communities have previously distinguished between expected personal outcomes and community-related outcomes while building on the privacy calculus model. We fill this gap and extend the model by conceptualizing, defining, and operationalizing these two dimensions of expected outcomes and examining their distinct impacts on PHI disclosure in VHCs.

With regard to affective commitment, extant literature related to social and clinical psychology in online and physical settings suggest that affective commitment (also known as emotional attachment), realized in terms of affection, connection, and passion (Chiu, Fang, & Wang, 2015; Thomson, Macinnis, & Park, 2005), is central in shaping one's interaction behaviors with individuals and groups to which one feels emotionally attached (Baumeister & Leary, 1995; Bowlby, 1979; Chiu et al., 2015). Accordingly, strong emotional attachment to an object can increase the likelihood of commitment to that object and making sacrifices for it (Hazan & Shaver, 1994). Accordingly, Rusbult and Buunk (1993) argue that willingness to sacrifice for the good of a relationship could be one of the key adults' behaviors in their relationships with their partners. Also, considering personal information disclosure a form of sacrifice in social behaviors, Greene, Derlega, and Mathews (2006) discovered that, in physical settings, people were more willing to disclose personal information to others with stronger social ties to them or to make such strong ties with them.

Similarly, in the context of online communications, prior research has shown that users of online social networks who feel a higher sense of belonging to these communities are more likely to participate in these networks and exert efforts to help others in the networks (Ren et al., 2012) even if no egoistic reasons exist for those helping behaviors (Mikulincer & Shaver, 2005). In a recent study, Chiu et al. (2015) found that emotional attachment (in voluntary organizations such as virtual communities in particular) can influence one's virtual community citizenship behaviors in terms of the extent to which one is willing to help and benefit individual members of an online community and the community as a whole. The authors discuss that individuals' citizenship behaviors in online communities would ultimately contribute to the overall effective functioning of those communities.

All in all, the results of prior studies have emphasized the prominent role of affective commitment in communication behaviors. Conversely, our findings showed that this construct may not significantly influence individuals' willingness to sacrifice their privacy and share their PHI while communicating with others in virtual environments. Moreover, our findings suggested that affective commitment in VHCs may not significantly intensify the relationship between one's expected positive community-related outcomes and one's willingness to PHI disclosure in online health communications. The divergence between the results of prior studies in online and offline social networks and the results of this study implies that the context of social networks in terms of mode (offline vs. online) and type (general-purpose vs. health-related) may change the impact of affective commitment on self-disclosure intention. In other words, although belongingness and emotional attachment may make people more willing to sacrifice in favor of their peers' and the community's benefit, that may not be true in VHCs. This result might also imply that, in contrast to most of the other forms of online and offline social groups and communities, VHC discussions revolve around short-term interactions, which are mainly formed based on temporary, need-based communications and not long-term, affect-oriented relationships. This implication is consistent with the relatively low mean value of affective commitment (mean = 3.18) in our dataset. Moreover, this conclusion is consistent with the results of Kordzadeh et al. (2014), which demonstrate that although people in VHCs exchange social support, they may not necessarily be interested in making long-term reciprocal relationships and social ties with their peers in those online communities.

In summary, our results extend our understanding of individuals' social behaviors in VHCs. Nevertheless, as we mention in the previous section, our findings did not rule out other social mechanisms through which affective commitment could play a role in VHCs such as by changing the balance between one's privacy concerns and perceived benefits of PHI disclosure online through influencing those constructs directly. In this way, the positive and negative sides of the privacy calculus model would hypothetically mediate the relationship between affective commitment and PHI disclosure in VHCs. Future research needs to address this hypothetical mediating relationship.

6.2 Practical Implications

The results of this study provide several implications for practice. The findings associated with the inhibitors side of the privacy calculus model demonstrated that developers, providers, and administrators of VHCs should address users' privacy concerns in order to motivate them to engage in activities related to seeking and providing social supports in these environments. Making online discussion forums private and accessible only to a segment of individuals (e.g., patients of a clinic and their families) and providing effective privacy settings and policy statements may mitigate individuals' privacy concerns to some extent. Websites' privacy protective actions and policies may be regulated and enforced at the government level by incorporating rules and guidelines into traditional policies such as HIPAA. In this way, government agencies such as the U.S. Department of Health and Human Services can guide VHCs and regulate their administrations on how they should enhance privacy of PHI shared on these websites.

Our results also showed that expected outcomes of communicating PHI may motivate individuals to contribute their health-related knowledge and experiences to online discussions. Thus, operators of VHCs can raise users' awareness on the potential benefits that exchanging health-related information on these communities may provide to them. Of course, one should do so only if VHC administrators believe that an adequate level of privacy protective policies and settings are in place and users are aware of privacy consequences of PHI disclosure in these communities. Otherwise, increasing users' intentions to communicate PHI may raise the privacy risks that they are subject to, which is not ultimately ethical.

6.3 Limitations and Future Research

This study also has several limitations. Although we used three sources for data collection, using students as part of the sample might reduce the generalizability of our results. Moreover, in this study, we did not require the respondents to be members of particular VHCs. Rather, we asked them if they were familiar with or member of any VHCs. In order to control for website-specific factors (e.g., privacy settings and policies, anonymity of users, and trustworthiness of website) that may potentially impact individuals' information sharing behaviors, researchers in future studies can collect data from individuals who are members of specific VHCs or are familiar with those specific websites.

Another limitation of this study is that we collected data from convenience samples, which we did not select randomly. This might entail selection bias. Future research can address this issue by selecting subjects randomly from different populations. Moreover, we measured the predictors and DV using the data collected via a single survey instrument. Thus, single method bias is still a potential threat to the validity of the results. In order to address this potential issue, future studies can test our research model by collecting measurement data via different methods. For example, one may collect data on actual behaviors of individuals on communicating PHI in public discussions directly from websites. This method of data collection may also widen the range of respondents in terms of affective commitment to the website. As a result, one could mitigate the marginal skewness of affective commitment values in this study.

The other limitation of this study is that, although we collected data on ethnicity and education, we did not include those variables in our regression models. The first reason for not including those variables in our analysis was that most of the respondents were either White or Hispanic; hence, our sample was not adequately distributed across different ethnical groups. Moreover, a majority of subjects were undergraduate students. Therefore, including ethnicity or education in the models might not reliably demonstrate the effects of those factors on the DV. Second, because our sample size was not very large, including more variables in the regression models would negatively impact the power of our analysis and would potentially make the results less reliable and unstable. However, future research can address this limitation by collecting more data from different ethnical groups at different levels of education to examine how those two factors may potentially impact individuals' willingness to share PHI in social media environments. Moreover, future studies can analyze the characteristics of individuals who are not familiar with VHCs and compare and contrast those characteristics with those of the individuals who are familiar with or members of VHCs. Finally, researchers in future studies can examine antecedents to PHI privacy concerns such as those listed in the discussion section including personality traits (Goldberg, 1993), socio-demographic variables, past positive or negative experiences related to personal information disclosure, and general awareness of privacy risks associated with information sharing in different environments.

7 Conclusion

In this study, we examined what factors impact willingness to communicate PHI in public VHC discussions. We proposed six hypotheses based on the privacy calculus model and the notion of affective commitment. To test the hypothesized relations, we collected data from students, faculty, and staff in the southern region of the United States and from patients of clinics in the University Hospital located in this region. The results of the two sets of MMR models showed that personal and community-related outcomes increased willingness to communicate PHI in online discussions. Moreover, our findings demonstrated that privacy concern associated with this form of information disclosure decreased individuals' willingness to engage in PHI communication activities in public VHC discussions. The results also refuted the hypothesized direct and moderating effects of affective commitment on PHI sharing in public discussions. The findings of this research study provide insights into the phenomenon of disclosing PHI in virtual environments and add to the literature on online social networks, information privacy, self-disclosure, and health informatics.

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Appendix: Regression Diagnostics

Linearity, normality, and homogeneity of variance (homoscedasticity) are the major three assumptions of linear regression models (Neter, Kutner, Nachtsheim, & Wasserman, 1996). Therefore, after running the MMR models in this study, we plotted and visually inspected various graphs to ensure that these assumptions were not violated in our analyses. The histograms, P-P normality plots, and predicted values versus residuals plots for each of the two MMR models (Equations 1 and 2) demonstrated that all the three assumptions were met in our regression analyses. Moreover, we conducted Shapiro-Wilk test (Shapiro & Wilk, 1965) to further check normality of residuals in both the models. The results revealed that the residuals in model 1 (p value = 0.377) and model 2 (p value = 0.527) were normally distributed. Also, we used a SPSS macro developed by Granero (2002) to conduct a Koenker test for heteroscedasticity (Koenker, 1981) on each of the models. The results associated with Equations 1 and 2 revealed that the test statistic values for those two models were 7.419 and 9.878 with p values equal to 0.4922 and 0.0788, respectively. These values indicated that the null hypothesis of homoscedasticity was not rejected for either of the models. Thus, from a statistical standpoint, heteroscedasticity was not an issue.

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