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Understanding Computer-Mediated Health Communication: Meta-Analytical Reviews of Social-Media-Based Interventions, Online Support Group, and Interactive Health

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UNDERSTANDING COMPUTER-MEDIATED HEALTH COMMUNICATION: META-ANALYTICAL REVIEWS OF SOCIAL-MEDIA-BASED INTERVENTIONS, ONLINE SUPPORT GROUP, AND INTERACTIVE HEALTH

By

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Computer-mediated communication (CMC) has been increasingly applied in health communication to provide interventions and education. A key question confronting health communication research is the effects of new technology on health communication. Despite the advantages of computer-mediated health communication (CMHC), the overall results of computer-mediated health interventions are mixed. To provide insights to CMHC scholars and generate cumulative knowledge, the current dissertation project consists of three meta-analytical reviews under the umbrella of CMHC. Specifically, three studies analyzed the general effectiveness of social-media-based health intervention, online support groups, and online interactive health interventions. Moreover, a series of moderator analyses were conducted to identify the variables that moderate the general effects of these three types of online health interventions. The identification of moderators will inform health communication scholars and practitioners in designing online health interventions.

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CHAPTER 1

INTRODUCTION

Health communication is the processes by which people understand, shape, and accommodate health and illness individually and collectively (Geist-Martin, Ray, & Sharf, 2003). While progress has been made in the past decades, health communication researchers are faced with new occurrences and challenges. An important issue is the growing application of new technologies in areas of health communication involving most stakeholders. For instance, medical providers are using Web 2.0 portal to disseminate health information and educate patients (Nordqvist, Hanberger, Timpka, & Nordfeldt, 2009), researchers are conducting web-based intervention to change health behaviors (Simon-Arndt, Hurtado, & Patriarca-Troyk, 2006; Stoddard et al., 2005; Whitten, Buis & Love, 2007), and patients are pursuing online support groups (Ancker et al., 2009; Tanis, 2008)

One primary way that people are involved in health communication is through the use of computer-mediated communication (CMC), which operates through computers and the Internet (Rheingold, 1993). In the last ten years, more people are turning to the Internet for information. The latest statistics by International Telecommunication Union (ITU, 2014) reported a 1,899 million growth in the number of worldwide Internet users from 16% in 2005 to 40% in 2014, reflecting a steady increase in the number of people utilizing the Web to seek information. Countries such as the United States have reflected a high Internet penetration for a number of years. According to the Pew Research Internet Project (2010), 74% of American adults are internet users, a figure that has remained stable since early 2006.

Given the increasingly important role that CMC provides in health communication, an important question confronting health communication research is the effects of new technology on health communication. Despite the advantages of computer-mediated health communication (CMHC), such as interactivity intervention, personalization, tailorization, or segmentation ability (Lustria, Brown, & Davis, 2007), the overall results of computer-mediated health interventions are mixed. Among the applications of CMC in health communication, three are of particular importance because of their broad reach and profound impact, namely the social-media-based health interventions, online support groups, and interventions with interactivity. In this study, systematic reviews of the computer-mediated health communication literature will be conducted to provide insights for these three topics and to examine the influence of CMC in communicating health messages.

Purpose of the Study

To achieve this goal, three meta-analyses will be conducted in the current study. Meta- analysis is a systematic methodological approach used to synthesize quantitative research findings (Noar, 2006), and is considered a useful tool to summarize a body of research and reconcile mixed findings (Hedges & Olkin, 1985; Hunter, Schmidt, & Jackson, 1982). The major purposes of meta-analysis are to determine: (a) magnitude of effect of a phenomenon, and (b) moderators of the effect. Meta-analytic reviews provide precise effect size, which move readers “away from the simple dichotomous language of whether a theoretical factor is significant or not, leading us to a more sophisticated analysis of the associations among variables” (Noar, 2006, p.173). However, despite the growth of health-related meta-analyses in the past decades (Lee, Bausell, & Berman, 2001), meta-analysis remains an underused tool in the communication discipline compared to other health-related areas (Hale & Dillard, 1991). Given the specific research goals and the strength of meta-analysis, it is considered an appropriate method for the current project, and will be applied in the following health communication areas.

First, the dramatic growth of Web 2.0 technologies and social media offers immense potential for the delivery of health behavior change interventions because of its: (a) broad reach that includes 1.1 billion users on Facebook each month (Techcrunch, 2013); (b) high level of engagement that one primary characteristic of social media is enabling users to actively engage and generate content (Thackeray, Neiger, Hanson & McKenzie, 2008); and (c) message delivery through existing contacts that were found to be more powerful than marketing strategies (De Bruyn & Lilien, 2008). The advantages of social media in facilitating health interventions have also gained the attention of heath communication scholars. For instance, Pechmann and her colleagues (2015) designed a smoking cessation intervention "Tweet 2 Quit" based on Twitter, using not only the user-generated tweets, but also auto-messages encouraging group discussion and providing individualized feedback to participants based on their past 24-hour tweeting. Despite the promising application of social media, the results of social-media-based interventions are mixed with effect sizes ranging from negative (e.g., Bull, Levine, Black, Schmiege, & Santelli, 2012; Turner-McGrievy & Tate, 2011) to 1.62 (Bull et al., 2012). Therefore, it is currently unclear which form of social media could be effectively harnessed to achieve health behavior change and how this would occur. Two major questions will be addressed: first, whether social-media-based interventions are effective overall; and second, whether the effect of interventions is moderated by factors, such as the media channel, health behavior type, and audience characteristics. A meta-analytic review is utilized to provide answers for these specific questions.

Second, another application of CMC in health communication is the online support group, where patients gain social support from other users. Social support is defined here as "verbal and nonverbal communication between recipients and providers that reduces uncertainty about the situation, the self, the other, or the relationship, and functions to enhance a perception of personal control in one's life experience" (Albrecht & Adelman, 1987, p. 19). Although Rains and Young (2009) meta-analyzed formal computer-mediated support groups (CMSG) to examine group characteristics and health outcomes, nearly 20 articles have subsequently been published due to the prevalence of CMSG. These recent studies focused on a variety of populations, such as cancer survivors (e.g., Duffecy, Sanford, Wagner, Begale, Nawacki, & Mohr, 2013; Høybye, Dalton, Deltour, Bidstrup, Frederiksen, & Johansen, 2010), caregivers of mental health patients (e.g., Clifford & Minnes, 2013; O'Connor, Arizmendi, & Kaszniak, 2014), and college students (e.g., Ellis, Campbell, Sethi, & O'Dea, 2011), producing effect sizes ranging from -.19 (Kim, 2013) to 1.33 (Ellis et al., 2011). Given the variation of the online support group designs conducted in recent years and their effects, the current meta-analysis is targeted to reexamine and extend this information.

Third, with interactivity being one of the major characteristics of CMHC (Lustria et al., 2007), the focus will be based on the increasing number of health communication studies that investigate using interactive health communication systems to conduct health education and promotion (e.g., Han, 2012; Weymann, Härter, & Dirmaier, 2013). One seminal work was conducted by Richardson and her colleagues (2013) who applied interactivity features to promote smoking abstinence. This interactive website was able to provide tailored plans for the users based on their progress and goals, identify and track smoking triggers, and form an online community with current and former smokers. This particular study was a success, however, the results of how well interactive health communication performs remain inconsistent with effect sizes ranging from -.55 (Riva, Camerini, Allam, & Schulz, 2014) to 2.10 (Danaher et al., 2013). Despite the encouragement of health communication scholars to conduct meta-analytic reviews of interactive health communication (Noar, 2006), one does not exist yet, and will be addressed in the current project. This study will provide an overall effect magnitude of interactive health communication applications conducted to date and explore potential moderators concerning the outcomes.

These three meta-analytic reviews are under the same umbrella of computer-mediated health communication, but differ in their foci. While social support group emphasizes reducing users' stress and improving their well-being, social-media-based and interactive interventions aim for health education and behavioral change. Interactive interventions can be between users themselves and users and websites, while the social media interventions can only be interactions between users.

Overview of the Study

This dissertation consists of five chapters. Chapter 1, Introduction, focuses on purpose of the current study by defining the issues, and presents relevant questions related to computer-mediated health communication. Chapter 2, Review of Literature, provides a brief overview of the three central aspects of this study: Health communication, computer-mediated communication, and computer-mediated health communication, as well as meta-analysis in health communication to focus on the rationalization of the current study. Chapter 3, Methods, elaborates on the procedures of the study, and explains why meta-analysis is considered an appropriate approach to address specific research questions generated in this study. Chapter 4, Results, describes the significance testing of the overall effects and moderator analyses. Chapter 5, Discussion, analyzes the hypotheses testing in the results section, describes the implications of the results, outlines limitation of the current study, and suggests direction for future research.

CHAPTER 2

REVIEW OF LITERATURE

This chapter reviews the relevant literature of health communication, computer-mediated communication (CMC), and computer-mediated health communication (CMHC). Under CMHC, online health intervention, an application of CMHC from health providers' perspective, is introduced. This present study systematically reviews three key topics — social-media-based health intervention, online support groups, interactive health interventions — of online health intervention. Thus, these three topics along with the problems under each topic are reviewed. Then, this chapter also describes meta-analysis and how this research method has been applied to health communication field so far.

Health Communication

Communication plays a fundamental role in public health because information brings knowledge to doctors and caregivers, and enables patients to be more powerful and confident to engage as partners with health service (Department of Health, 2004). Therefore, attention to communication when addressing health issues is warranted. Health communication is "the symbolic processes by which people, individually and collectively, understand, shape, and accommodate to health and illness" (Geist-Martin, Ray, & Sharf, 2003, p. 3). It is defined by the National Communication Association (2014) as the study of communication related to health professionals and health education, including the diffusion of information through public health campaigns and health educations, and provider-patients interaction. Health communication is a broad topic because: (a) there are different types of relationships; (b) communication can take place between many different players; and (c) communication is affected by each person's role and his/her expectation of others in the health care process (Berry, 2006). Therefore, collaboration is crucial in health communication research and practice. Without external funds and collaborative work, health communication alone may only make limited effects, if any, at sustaining health behavior changes (Freimuth & Quinn, 2004).

Computer-Mediated Communication

One way that health communication takes place is through the use of computer-mediated communication, which can be defined as forms of communication that operate through computers and telecommunications networks (Rheingold, 1993). The term did not appear until the Second World War when the first electronic digital computer was invented. Computer-mediated communication application and research did not gain popularity until the mid-1990s because of the ubiquity of personal computers and activities such as emailing, chatting and surfing. Although CMC was originally referred to communication that occurred via the computer-mediated formats, it has also been applied to other forms of text-based interaction such as text messaging (Thurlow, Lengel, & Tomic 2004).

With the rapid development of communication technologies changing the way people interact with each other, a major area of CMC research has focused on interpersonal communication via social media. The variety of new features brought by technology, such as user-generated content, many-to-many communication, high-level of anonymity and compromise of credibility, motivated a large amount of scholarly work investigating the influences of these features (e.g., Toma & Hancock, 2010; Walther, Van

Der Heide, Hamel & Shulman, 2009). Computer-mediated communication has also been studied broadly in communication research, not only in health communication (e.g., Lee, Lee, Choi, Kim, & Han, 2014), but also in areas such as political communication (e.g., Halpern & Gibbs, 2013), organizational commutation (e.g., Treem & Leonardi, 2012), and intercultural communication (e.g., Mollov & Schwartz, 2010).

Computer-Mediated Health Communication

The application of CMC specifically to health has been referred to as computer-mediated health communication (Lustria et al., 2007), including "interactive health communication," "web-based interventions," or "eHealth." Interactive health communication is the interaction between consumers, patients, caregivers, or professionals through communication technology to acquire or transmit health-related information or to receive guidance and support on a health-related issue (Robinson, Patrick, Eng, & Gustafson, 1998). This term was later replaced by "eHealth" (Noar & Harrington, 2012), which was defined as "the use of emerging information and communication technology, especially the Internet, to improve or enable health and health care" (Eng, 2001, p.1).

One major application of computer-mediated health communication is that physicians allow patients to incorporate information from the Internet into medical consultations (Ahmad, Hudak, Levinson, Bercovitz, & Hollenberg, 2006). Although some physicians appreciate adding health-related Internet information (HRII) to consultations (Sommerhalder, Abraham, Zufferey, Barth, & Abel, 2009), it can also create misinformation and misinterpretations leading to confusion, distress, and inaccurate self-diagnoses and self-treatment (Ahmad et al., 2006). Similarly, mixed results were obtained in web-based interventions, another application of computer-mediated health communication. Lustria, Brown and Davis (2007) conducted a ten-year review of the literature regarding online interventions and found that successful web-based interventions shared similar characteristics, such as solid theoretical framework, taking advantage of web delivery, engaging audiences, and institutional buy-in.

Online Health Intervention

Health interventions implemented online are also referred to as e-health. "E-health" was defined as "the use of emerging information and communication technology, especially the Internet, to improve or enable health and health care" (Eng, 2001, p.1). E-health strategies are becoming an important part of the strategies for those in health education and health behavior (Noar & Harrington, 2012) and are usually implemented through computer and Internet, mobile phone, and social media.

Internet and computer-based applications, along with wireless technologies, can support many of the health behavior and health education strategies. They are described as "primarily self-guided, interactive Web-based programs, created with the goals of assisting users to make behavior changes that will prevent disease, monitor health status, and/or improve response to clinical treatment" (Buller & Floyd, 2012, p.59). Such interventions are widely used in a variety of topics, such as helping people to quit smoking, increasing physical exercise, reducing alcohol use, and losing weight.

Online interventions on mobile phones are usually implemented through text messaging and apps. Text messaging can be compelling because of the huge saturation of mobile phones in today's society and the fact that people have mobile phones with them most of the time. Text messaging is applied in health interventions to: (a) enhance the use of health services, (b) deliver health messages, (c) manage chronic disease, and (d) deliver personalized health promotion messages (Fjeldsoe, Miller, & Marshall, 2012). Health apps are the software programs that are available on smart phones, such as iPhone and Android, and used for mobile health promotion. However, health apps have rarely been rigorously evaluated (Abroms, Padmanabhan, & Evans, 2012).

Health messages of online health interventions differ from those of traditional health interventions in the following key aspects. First, online health interventions are able to design health messages using multiple forms of media, such as images, video, sounds, etc. Second, online health messages have the potential to be tailored according to the receiver's personal characteristics. Third, messages in online health interventions are more flexible to be changed and modified, relatively easy to be updated, and are disseminated at lower cost. Fourth, messages can be more informative in online health interventions, providing users with opportunity to access vast amount of health information.

Social Media in Public Health

The past decade witnessed the increase of using Internet and social media in public health. One-third of adults access health-related social media, and approximately 25% of physicians use social media channels to create, consume, or share medical content (Fox, 2011; McGowa, Wasko, Vartabedian, Miller, Freiherr, & Abdolrasulnia, 2012). Social marketing theory (Andreasen, 1994; Maibach, Rothschild & Novelli, 2002) has been incorporated into communication research with the increase of social media. Specifically, audience segmentation is applied which involves analyzing intended audiences and identifying distinct subgroups with similar needs, attitude or behaviors.

This theory focuses on the knowledge of how and where audiences access online information about the issue in question, preferred social media networks, and use of networks that are critical for an intervention to succeed.

Resulting from web-based and mobile technologies, social media can take a variety of forms, including Internet forums, message boards, social network sites (e.g., Facebook, Twitter, MySpace), texting via mobile devices, and blogs. According to Neiger and colleagues (2012), social media are used in online health interventions for the following purposes: (a) To “listen” to consumers and learn about their thoughts about a particular health issue, (b) to establish and promote a health brand, (c) to disseminate information to the public, (d) to expand the reach of a health communication initiate or campaign, and (e) to foster public engagement. Despite these different forms, the role of social media in public health is less about the technology per se, and more about the way individuals are empowered to interact with others online (Hughes, 2010). Whether or not social media has been effectively applied to health interventions is a crucial issue to investigate for public health scholars and professionals.

Health Online Support Groups

Social support, a term that describes the association between participation in social relationships and one’s well-being (Albrecht & Goldsmith, 2003; Barrera, 1986; Goldsmith, 2004), has been defined as ‘‘verbal and nonverbal communication between recipients and providers that reduces uncertainty about the situation, the self, the other, or the relationship, and functions to enhance a perception of personal control in one’s life experience’’ (Albrecht & Adelman, 1987, p. 19). In most cases, social support is based on mutual reciprocation within the interpersonal relationship (Egbert, Koch, Coeling, &

Ayers, 2006). Social support is always intended and consciously provided to be helpful, which distinguishes it from intentional negative interactions and unintentional behaviors (Heaney & Israel, 2008). According to House (1981), social support is the functional content of relationships that can be categorized into four broad types of supportive behaviors: (a) *emotional support,* the provision of empathy, love, trust, and caring; (b) *instrumental support*, the provision of tangible aid and services that directly assist a person in need; (c) *informational support*, the provision of advice, suggestions, and information that a person can use to address problems; and (d) *appraisal support*, the provision of constructive feedback and affirmation.

The central idea of support groups is that people confronted with similar situations are in unique positions to understand each other in ways that friends or family may not (Helgeson & Gottlieb, 2000). Based on the buffering model and the main effect model (Cohen & Wills, 1985), Helgeson and Gottlieb (2000) pointed out that sharing experiences with others based on similar stressors is “expected to lead to validation, normalization of the experience, a reduction in emotional isolation, and a sense of belonging” (p.225). Segrin and Passalacqua (2010) using a theory of loneliness and health outcomes explored how social support can facilitate beneficial health outcomes, and found that loneliness is a functional mediator in this relationship—the more social support people receive, the less lonely they are, and the less lonely they are, the more healthy they are in general. Moreover, they also found that the relationship between loneliness and health is mediated by perceived stress and specific health behaviors (e.g., exercise and diet). Despite the advantages of social support groups in improving mental and physical health, there are research showing that some people feel reluctant to join a support group or drop out after at an early stage (Gottlieb & Wachala, 2007) and some participants may experience worse outcomes (Galinsky & Schopler, 1994; Helgeson, Cohen, Schulz, & Yasko, 2000). Demographic variables, such as age, gender, race, and ethnicity also influence the effect of social support groups on health outcomes (Pedersen, Olesen, Hansen, Zachariae, & Vedsted, 2011; Wittenberg-Lyles, Goldsmith, & Shaunfield, 2015).

Online support groups, also referred to as computer-mediated support groups, are delivered by medical professionals using the Internet and consisting of an educational component and a group communication component. Although rooted in the same basic principles as face-to-face support groups, computer-mediated support groups have the potential to capitalize on the unique features of computer-mediated communication, such as increased access to support, greater ability to manage interactions and reduced social cues (Braithwaite, Waldron & Finn, 1999; Shaw, McTavish, Hawkins, Gustafson, & Pingree, 2000; Walther & Boyd, 2002; Wright & Bell, 2003). Online support groups were found as a way to improve participants' health outcomes by reducing stress, increasing positive coping, increasing quality of life, increasing self-efficacy in managing health problems, reducing depression, and increasing physical health benefits (Beaudoin & Tao, 2007; Fogel, Albert, Schnabel, Ditkoff, & Neugut, 2002; Gustafson et al., 2005; Houston, Cooper, & Ford, 2002; Jones et al., 2008; Owen et al. 2005; Rains & Young, 2009; Shaw, Hawkins, McTavish, Pingree, & Gustafson, 2006; Wright, 1999, 2000).

There are several key features that set online support groups apart from face-to-face support groups: (a) anonymity, (b) asynchronization, (c) access to multiple perspectives, and (d) text-based communication.

Anonymity. Because of the anonymity in online social support groups, individuals are not visible to other group members. This is particularly helpful for people with rare or stigmatized health conditions or people who have difficulty developing close face-to-face relationships (Wright, 2002a, 2002b). On the flip side, however, the lack of nonverbal social cues and reduced social presence can create the potential for hostile messages and difficulties in contacting a specific person for additional information, emotional support, or developing an ongoing long-term relationship (Wright & Bell, 2003).

Asynchronization. The asynchronous communication allows individuals to use and get access to group information at times and locations of their choosing. This feature provides users with time and space independence and flexibility in when to read and write social support messages. However, as a cost of asynchronous communication, the lack of immediacy can frustrate participants when they are communicating with others.

Access to multiple perspectives. Compared to face-to-face communication, people were able to communicate with a wider variety of people (Finn & Lavitt, 1994), and therefore receive information from an assortment of people. Such connectivity to a large, weak-tie network of people who have diverse backgrounds, similar experiences, and varied attitudes not only makes multiple sources of information and diverse viewpoints available to the participants, but also becomes beneficial in mitigating stress, providing emotional support, and meeting informational needs in times of crisis (Sen, 2008).

Text-based communication. The text-based communication medium was found to provide an additional therapeutic advantage and remove the immediate face-to-face reactions of others, offering an environment for the discussion of sensitive topics (Campbell & Wright, 2002; Wright, 2002a, 2002b). However, such form of communication was found lack of interpersonal physicality, greater relational intimacy, and ability to provide tangible support (Colvin, Chenoweth, Bold, & Harding, 2004).

Interactivity in Public Health

Given the potential of eHealth to achieve both high efficacy and greater reach, researchers found that the use of interactivity is the most notable feature to make eHealth applications persuasive (Cassell, Jackson, & Cheuvront, 1998). *Interactivity* is the ability of users to communicate via websites by collecting their information and adjusting content, resources, and advice to personalize the service (Burgoon, Bonito, Bengtsson, Cederberg, Lundeberg, & Allspach, 2000; Heeter, 1989; Rice & Katz, 2003; Rogers & Albritton, 1995). Communication technologies that deliver interactive features are mostly websites, mobile phones, and social media. According to Kiousis (2002), interactivity in online health interventions is the degree “to which a communication technology can create a mediated environment in which participants can communicated (one-to-one, one-to-many, and many-to-many), both synchronously and asynchronously, and participate in reciprocal message exchanges” (p. 372). Moreover, interactivity can also provide an experience as a simulation of interpersonal communication (Kiousis, 2002), which is an important opportunity especially in the absence of human interaction. Since computer-mediated communication “enable[s] users to access information and services of interest, control how the information is presented, and respond to information and messages in the mediated environment" (Street & Rimal, 1997, p. 2), interactive technology has created new possibilities for health communication to overcome barriers such as low literacy and expand opportunities to tailor and personalize information (Freimuth & Quinn, 2004).

Interactivity was found to play a significant role in eHealth efficacy and health behavior change from both theoretical and empirical perspectives (Cassell, Jackson. & Cheuvront, 1998; Hawkins, Han, Pingree, Shaw, Baker, & Roberts, 2010). Interactivity can be categorized into *medium interactivity* and *human interactivity. Medium interactivity* refers to the cases where users interact with a computer, such as interactive website, health video game, health app (Hawkins et al., 2010). One pioneering application of interactive health interventions, the Comprehensive Health Enhancement Support System (CHESS), showed impressive research evidence of its potential for reducing disparities (Hawkins et al., 1997). Other contemporary examples make better use of this technology. For instance, the Wii *Fit* game made good use of adaptive tools, which allow personalization and customization options for various users (Sundar, Xu, & Bellur, 2010). Through the use of avatars, participants could extend their personal identities through a computer interface, and modify their avatars' characteristics. Another interactive feature in online health interventions is *human interactivity*, where people interact with each other through media, such as chat room, social media, and text messaging (Tate, Jackvony, & Wing, 2006). Researchers also found positive effects of human interactivity applied to online health contexts, such as facilitating information sharing (Schultz, Stava, Beck, & Vassilopoulou-Selllin, 2003) and improving gratifications (Chung & Kim, 2008). Since information and communication technologies "enable users to access information and services of interest, control how the information is presented, and respond to information and messages in the mediated environment" (Street & Rimal, 1997, p. 2), interactive technology has created new opportunities for health communication that overcome barriers such as low literacy and expand opportunities to tailor and personalize information (Freimuth & Quinn, 2004).

Besides investigation of the general effect, previous research (i.e., Noar, Benac, & Harris, 2007; Snyder, Hamilton, Mitchell, Kiwanuka-Tondo, Fleming-Milici, & Proctor, 2004) suggests that health topic, participant's features (e.g., age, gender, social-economic status [SES], health condition), type of outcomes, publication year, and intervention features could moderate the effects of health interventions. Therefore, these variables suggested by previous meta-analytic reviews concerning features of the publication, study design, and participants will be analyzed in the current project as potential moderators. In addition, selected topic-specific features will also be analyzed. For instance, some interventions are based on social media only (e.g., Bull et al., 2012), while other studies are multimodally designed with social media and other platforms (e.g., Cobb & Poirier, 2014). Similarly, some online support groups were conducted in a synchronous way (e.g., Clifford & Minnes, 2013), while others in an asynchronous way (e.g., Crisp, Griffiths, Mackinnon, Bennett, & Christensen, 2014). Since empirical CMHC research (Hu & Sundar, 2010) indicated that media platform matters in influencing the results, such topic-specific technology features were also included in the meta-analysis as potential moderators.

Meta-Analysis in Health Communication

Meta-analysis is "the statistical analysis of a large collection of analysis results from individual studies for purposes of integrating the findings" (Glass, 1976, p.3). Meta- analysis, a systematic approach to research synthesis focusing on the quantitative integration of research findings (Noar, 2006), is considered as a useful tool to summarize a body of research and reconcile mixed findings (Hedges & Olkin, 1985; Hunter, Schmidt, & Jackson, 1982). The major purposes of meta-analysis are to determine: (a) magnitude of effect of a phenomenon, and (b) moderators of the effect. Meta-analytic reviews provide precise effect size (ES), which move readers “away from the simple dichotomous language of whether a theoretical factor is significant or not”, and lead us to “a more sophisticated analysis of the associations among variables” (Noar, 2006, p.173). Effect size is regarded as superior to statistical significance because: (a) such estimates are more precise, and (b) unlike statistical significance tests, such estimates are independent of sample size (Borenstein, Hedges, Higgins, & Rothstein, 2009).

Meta-analysis enjoys several advantages over traditional narrative review of literature. First, effect size is viewed as superior to statistical significance because: (a) such estimates are more precise and sophisticated, and (b) unlike statistical significance tests, such estimates are independent of sample size (Noar, 2006). Second, meta-analytic review, the quantitative synthesis of ESs, can handle a large numbers of studies, which would overwhelm traditional review approaches in a narrative way. Third, the influence of the study contexts can be examined across studies. In meta-analytic reviews, study contexts can be quantified and evaluated in moderator analysis to explain the heterogeneity of study effects. Fourth, because the sample size in meta-analysis is the sum of sample sizes of all the reviewed studies, this method can reduce sampling error and increase statistical power. Thus, the precision of effect estimates is also increased.

Since the introduction of meta-analysis, health sciences witnessed an explosion of applying this research method (Bausell, Li, Gau, & Soeken, 1995; Lee, Bausell, & Berman, 2001; Lyman & Kuderer, 2005). For instance, using Medline as a search tool, Lee and his colleagues (2001) found a linear growth of health-related meta-analyses in the published literature between 1980 and 2000, with approximately 400 newly published meta-analyses in the year 2000. Despite the growth of health-related meta-analyses in the past decades (Lee et al., 2001), meta-analysis remains an underused tool in the communication discipline compared to other health-related areas (Hale & Dillard, 1991). An examination of journal issues through the end of 2014 yielded only two meta-analyses published in *Health Communication* (Carpenter, 2010; O'Keefe & Nan; 2012), while five meta-analyses were published in *Journal of Health Communication* (Casey et al., 2003; Lustria, Noar, Cortese, Van Stee, Glueckauf, & Lee, J., 2013; Noar, Carlyle, & Cole, 2006; O'Keefe & Jensen, 2007; Snyder et al., 2004). Although six meta-analyses were published in other journals (Emmers-Sommer & Allen, 2001; Snyder, Hamilton, & Huedo-Medina, 2009; Henry, Fuhrel-Forbis, Rogers, & Eggly, 2012; Keller & Lehmann, 2008; Rains & Young, 2009; Wanyonyi, Themessi-Huber, Humphris, & Freeman, 2011), this method still remained underused in the communication discipline (Hale & Dillard, 1991). Since a major goal of health communication is to build cumulative knowledge in this area, meta-analysis has been found as a powerful approach to achieve this goal (Noar, 2006).

In the next chapter, implementation of meta-analytic review for the current project will be detailed. Specific discuss includes the literature search, overview of meta-analysis procedure, and correction for artifacts.

CHAPTER 3

METHOD

Literature Search

Comprehensive searches of the Communication & Mass Media Complete, PsycINFO, Web of Knowledge, PubMed and Medline databases were used to identify for potential eligible studies in English-language peer-reviewed journals and conference proceedings. No year range was set because both online and offline health message studies were included in this study. Search queries for all three meta-analyses were formulated using combinations of the following terms: Study 1 (social-media-based interventions) — “intervention” (Title) AND “health” (Title/Abstract) AND “social media” OR “social network*” (Facebook OR LinkedIn OR Twitter OR Tencent OR Weibo OR MySpace) (Title/Abstract); (b) Study 2 (computer-mediated support groups) — “health” (Title/Abstract) AND "online support group" ("computer-mediated support group" OR "Internet support group" OR "Internet self-help group") (Title/Abstract); and Study 3 (interactive health interventions) – interactive health—“health” (Title/Abstract) AND “intervention” (Title) AND “interactive OR interactivity” (Title/Abstract) AND “web-based/internet-based” (Title/Abstract). All potential eligible articles were examined to determine the extent of relevance. Studies were screened in several stages using explicit inclusion and exclusion criteria: (1) Published in English-language, peer-reviewed journals or conference proceedings; (2) quantitative studies using randomized controlled trials (RCT) or surveys; and (3) effect sizes or sufficient statistical information available for calculation. (See Figures 1-3 for illustration of this process of each meta-analysis, and Tables 1-3 for list of studies included in each meta-analysis.)

Citations were evaluated for including qualified studies. Studies not published in English language or duplicated publications were excluded. Abstracts of the remaining potentially eligible studies were closely examined for relevance. Studies that fail to provide enough statistical information for effect sizes computation and studies that are not randomized controlled trials or survey in methodology were also excluded.

Overview of Meta-Analysis

As generally recommended in the methodological literature regarding meta-analysis (Hunter & Schmidt, 2004; Rosenthal, 1991), Cohen's *d* was computed as the basic unit of analysis for the systematic review. The statistical analyses were based on methods proposed by Hedges and Olkin (1985) and also described in Cooper, Hedges, and Valentine (2009). The current meta-analyses used the variance-weighted analyses (Hedges & Olkin, 1985) and, therefore, under the fixed-effect model, the overall weighted correlation between variables was computed by weighting the unbiased effect size (r) by the inverse of its associated variance ($v_{(r)i}$). An overall homogeneity test of effects using Q statistics was used to determine whether all effects were from the same population. If the Q statistics were statistically significant, which indicated that the effects sizes were not from the same population, the overall effect sizes were computed under the random effects models, which incorporate additional between-studies uncertainty to the effect sizes (Raudenbush, 2009).

Given the significant Q statistics, which indicated the heterogeneity of effect sizes in the current sample, a number of characteristics for the studies were coded for potential moderators including: (a) Group size, (b) publication year, (c) sample type (student/non-student), (d) percentage of male participants, and (e) participants' age (*M* and *SD*). Group size was coded because network size has been related to positive outcomes (Franks, Cronan, & Oliver, 2004; Gielen, McDonnell, Wu, O'Campo, & Faden, 2001; Shye, Mullooly, Freeborn, & Pope, 1995). Publication year was coded as a potential moderator because the increasing knowledge of researchers and sophistication of research designs may result in higher effect sizes (Cohen, 1988). Moreover, whether the studies were conducted with student samples can potentially moderate the effect sizes, given the long-lasting argument that students are not representative of the general population (e.g., Briggs & Nebes, 1975; Falk & Heckman, 2009). Finally, demographic variables were also coded for investigation of potential moderators.

In the moderator analysis, ANOVA-like categorical models were conducted to analyze categorical moderators (e.g., publication tier, sample type). $Q_{between}$ statistics was applied to explore if study features explain between-group variations in effect sizes. If $Q_{between}$ was significant while Q_{within} was not, then it was concluded that this moderator explained the total variances, and stuck to the fixed-effect model. However, when both $Q_{between}$ and Q_{within} were significant, there were still unexplained variances left, so mixed-effect models[1] with moderators were performed. The same logic was applied when using a regression model to analyze continuous moderators (e.g., publication year, percentage of male participants). In the cases that moderator analysis were statistically significant ($Q_{between}$ statistics were significant under the mixed-effect model), post-hoc analysis was conducted for further investigation.

The next chapter will detail the results obtained by following the aforementioned procedures. Results for Study 1, Study 2, and Study 3 will be presented separately. The study description, check for publication bias, overall analysis, and moderator analysis will be detailed for each study.

CHAPTER 4

RESULTS

Study 1

Study Description

A total of 12 studies were included in Study 1 meta-analysis. The studies analyzed, sample size, dependent variable constructs, participants' mean age, and effect sizes (*d*) employed reported in Table 4. For the experimental studies that have multiple effect sizes produced by multiple conditions, they were treated as separate studies by following Schmidt and Hunter's (1999) approach. Therefore, 53 effect sizes were analyzed. Among these 12 articles which were published during 2010 to 2014, three appeared in the American *Journal of Preventive Medicine* (Bull et al., 2012; Cavallo, Tate, Ries, Brown, DeVellis, & Ammerman, 2012; Cobb & Poirier, 2014), two in *Social Psychiatry and Psychiatric Epidemiology* (Livingston, Cianfrone, Korf-Uzan, & Coniglio, 2014; Livingston,Tugwell, Korf-Uzan, Cianfrone, Coniglio, 2014), two in *Journal of Medical Internet Research* (Brindal, Freyne, Saunders, Berkovsky, Smith, & Noakes, 2012; Turner-McGrievy & Tate, 2011), one in *Obesity* (Napolitano, Hayes, Bennett, Ives, & Foster, 2013), one in *Medical and Care Compunetics* (Kuwata et al., 2010), one in *Journal of Cancer Survivorship* (Valle, Tate, Mayer, Allicock, & Cai, 2013), and two are conference proceedings (Foster, Linehan, Kirman, Lawson, & James, 2010; Freyne, Berkovsky, Kimani, & Brindal, 2010). Among these studies, one study focused on young adult cancer survivors (Valle et al., 2013), two studies used student samples (Cavallo et al., 2012; Napolitano et al., 2013), three studies used sample of teenagers and young adults (Bull et al., 2012; Livingston et al., 2013, 2014), four studies focused on overweight adults (Brindal et al., 2012; Kuwata et al., 2010; Napolitano et al., 2013; Turner-McGrievy et al., 2011), and other studies focused on general adults. In total, 5935 (N = 5935) participants were included. Except for Kuwata and his colleagues' study (2010), most studies have more female participants than male participants.

Publication Bias

Publication bias may exist when the publication status depends on the statistical significance of study results (Sutton, 2009). There are multiple ways to check for a potential publication bias problem. First, a funnel plot can be used for examination of whether effect sizes from smaller studies show more variability than those from larger studies. As shown in Figure 4, the funnel plot of effect sizes seems to be generally symmetric, which provides evidence for the absence of publication bias. Further, the Egger's regression test for funnel plot asymmetry was not statistically significant (z = 1.10, p = 0.27), indicating that publication bias probably does not exist in this sample. Moreover, Rosenthal's Fail-safe N was 2, 467, which is larger than the tolerance level ($5k$ + 10 = 275), and further confirmed the absence of publication bias.

Overall Analysis

Q statistics were applied to examine whether the effect sizes were from the same population. Because Q_{total} was significant (Q_{total} (df = 52) = 1293.22, p < .001), the effect sizes were not homogeneous, and mean effect size under the random-effect model was estimated by Restricted Maximum Likelihood Estimation (REML) method. Under the REML model, the sample weighted mean for uncorrected correlation coefficients was 0.169 (N = 5935, K = 38, 95% CIs [.05, .28]), which is regarded as small effect size (Cohen, 1988), but statistically significance (p < .01). In other words, there were statistically significant mean differences between the treatment and control groups according to the overall analysis. Moreover, I^2, an index representing the ratio of true heterogeneity to total variance across observed effect sizes, is 95.99%, which shows large between-study variance in this case. Similarly, Birge's ratio, another index to quantify the magnitude of heterogeneity, is computed as Q/df = 1293.22/ 52 = 24.87. Since Birge's ratio is much larger than one (which is ratio when all the variance comes from sampling error), we can conclude that the between-study heterogeneity is large in this study. Sampling error variance (S_e^2 = 0.009) only accounted for 6.04% of the total variance (S^2 = 0.1552), indicating the presence of moderator(s). Therefore, the hypothesized categorical and continuous moderators were analyzed.

Moderator Analysis

Given the significant Q statistics, which indicates heterogeneity of the effect sizes across these 53 studies, moderator analyses were conducted with subgroup (1_normal adults; 2_overweight adults; 3_normal teenagers and young adults; 4_ young adult cancer survivors), channel (1_SM only; 2_SM+Website; 3_Multimodal (with mobile device), topic (1_obesity/overweight; 2_ physical activity; 3_ mental health and wellbeing; 4_ sexual health; 5_health info), outcome (1_target outcome 2_cognitive [e.g., self-efficacy, awareness]; 3_attitude; 4_well-being), and measure (1_continuous multiple; 2_continuous single; 3_categorical) being analyzed as categorical moderators respectively.

Under fixed-effects model, subgroup as a moderator is not significant $Q_{between}$ (df = 3) = 4.96, p = .18, and no follow-up analysis is needed. Channel as a moderator is also not significant $Q_{between}$ (df = 2) = 1.54, p = .46, with no follow-up analysis needed.

Regarding topic as a potential moderator, both the between-study variance ($Q_{between}$ (4) = 73.64, $p < .001$) and the test of heterogeneity (Q_{within} (48) = 1219.59, $p < .001$) are statistically significant under the fixed-effect model, which indicates that topic could potentially be a moderator, but cannot explain all the variation across the studies. Therefore, mixed effect model was used for moderator analysis. However, under the mixed-effects model, the moderator test was no longer significant ($Q_{between}$ (4) = .91, p =.92). Similarly, the between-study variance of outcome was significant under fixed-effect model ($Q_{between}$ (3) = 44.66, $p < .001$), but not under the mixed-effect mode ($Q_{between}$ (3) = 2.6596, p =.45), indicating that outcome was not a significant moderator. For measure as a potential moderator, given the significant between-study variance under the fixed-effect model ($Q_{between}$ (2) = 92.00, $p < .001$), the moderator analysis was conducted under a mixed-effect model. Under mixed-effect model, the $Q_{between}$ was marginally significant, $Q_{between}$ (df = 2) = 5.63, p = .06. Therefore, measure was a significant moderator of the effect sizes; studies with categorically measured outcome variables have significantly higher effect sizes (d = .50, SE = .26, K = 6, 95% CIs [-.013, 1.014]) than those with outcome variables being continuously measured (d = .081, SE = .06, K = 28, 95% CIs [-.035, .197]) ($p < .05$).

In terms of continuous moderators, neither participants' average age ($Q_{between}$ (df =1) = .90, p = .34) nor the percentage of female participants ($Q_{between}$ (df = 1) = 1.29, p =.26) were a significant moderator because of the nonsignificant between-study variance under the fixed-effect model. However, the evaluation time was a significant continuous moderator, with moderator test significant ($Q_{between}$ (df = 1) = 4.834, $p < .05$). The estimated intercept and slope were .34 (SE = .10, K = 53, 95% CIs [.149, .524]) and -.01

(*SE* = .004, *K* = 53, 95% CIs [-.02, .001]), and were statistically significant. The estimated mean effect size decreases by .01 given an additional week after the intervention.

Study 2

Study Description

A total of 15 studies were included in Study 2 meta-analysis. The studies analyzed, group size, participants' mean age, and effect sizes (*d*) employed reported in Table 5 to Table 8 for dependent variable constructs of depression, social support, quality of life, and self-efficacy respectively. For the experimental studies that have multiple effect sizes produced by multiple conditions, they were treated as separate studies by following Schmidt and Hunter's (1999) approach. In total, 42 effect sizes were analyzed, of which 19 effect sizes for depression, 7 for social support, 11 for quality of life, and 5 for self-efficacy. Among these 15 articles, which were published after 2009, one appeared in the *Journal of Medical Internet Research* (i.e., Bantum et al., 2014), three in the *Psycho-Oncology* (i.e., Classen et al., 2013; Duffecy et al., 2013; Salzer et al., 2010), one in the *Journal of Autism and Developmental Disorders* (i.e., Clifford& Minnes, 2013), one in the *Psychiatry Research* (i.e., Crisp et al., 2014), one in the *Journal of Cybertherapy and Rehabilitation* (i.e., Ellis et al., 2011), one in *Plos One* (i.e., Griffiths, Mackinnon, Crisp, Christensen, Bennett, & Farrer, 2012), one in the *British Journal of Cancer* (i.e., Høybye et al., 2010), one in *Computers, Informatics, Nursing* (i.e., Klemm, 2012), one in the *Journal of Aging Studies* (i.e., O'Connor et al., 2014) [2], one in the *Urologic Nursing* (i.e., Osei, Lee, Modest, & Pothier, 2013), one in the *Health Psychology* (i.e., Stice, Durant, Rohde, & Shaw, 2014), one in the *Journal of Consulting and Clinical Psychology* (i.e., Stice, Rohde, Durant, & Shaw, 2012), and one is an unpublished dissertation (Kim, 2013).

All these studies focused on at-risk population, except for one study conducted with dementia caregivers instead of patients (O'Connor et al., 2014). Student samples were used in three studies (Ellis et al., 2011; Stice et al., 2012, 2014), while other studies examined adults in general. Seven studies (Classen et al., 2013; Kim, 2013; Klemm, 2012; O'Connor et al., 2014; Stice et al., 2012, 2014; Salzer et al., 2010), most of which investigated gynecologic diseases, only included female participants. One study (Osei et al., 2013) on prostate cancer only included male participants. In total, 3,501 (N = 3,501) participants were included in the meta-analysis.

Publication Bias

Publication bias may exist when the publication status depends on the statistical significance of study results (Sutton 2009). There are multiple ways to check for a potential publication bias problem. First, a funnel plot can be used for examination of whether effect sizes from smaller studies show more variability than those from larger studies. As shown in Figure 5, the funnel plot of effect sizes seems to be a little bit asymmetric, which provides evidence for the possibility of publication bias. Moreover, the Egger's regression test for funnel plot asymmetry was statistically significant (z = 3.00, p <. 05), indicating that publication bias probably exists in this sample. However, Rosenthal's Fail-safe N was 745, which is larger than the tolerance level ($5k + 10 = 220$), indicating the absence of publication bias. Given the mixed results of publication bias tests, there was the possibility that publication bias exists and caution needs to be taken when drawing conclusions.

Overall Analysis

Q statistics was applied to examine whether the effect sizes were from the same population. Because Q_{total} was significant (Q_{total} (df = 41) = 82.61, $p < .001$), the effect sizes were not homogeneous, and mean effect size under the random-effect model was estimated by Restricted Maximum Likelihood Estimation (REML) method. Under the REML model, the sample weighted mean for standardized mean difference was 0. 21 (N = 3,501, K = 42, 95% CIs [.12, .30]), which is regarded as small effect size (Cohen, 1988), but statistically significance ($p < .01$). In other words, there was statistically significant mean difference in outcome variables for participants in the computer-mediated support groups (CMSGs) when measured at the baseline and after the intervention according to the overall analysis. Moreover, I^2, an index representing the ratio of true heterogeneity to total variance across observed effect sizes, is 53.79%, which shows medium to large between-study variance in this case. Similarly, Birge's ratio, another index to quantify the magnitude of heterogeneity, is computed as Q/df = 82.61/ 41 = 2.07. Since Birge's ratio was larger than one (which is ratio when all the variance comes from sampling error), we can conclude that the between-study heterogeneity was adequate in this study. Sampling error variance (S_e^2 = 0.0373) only accounted for 1.73 % of the total variance (S^2 = 2.16), indicating the presence of moderator(s). Therefore, the hypothesized categorical and continuous moderators were analyzed.

Moderator Analysis

Given the significant Q statistics, which indicates heterogeneity of the effect sizes across these 15 studies with 42 effect sizes, moderator analyses were conducted with *topic* [3] (1_chronic disease [e.g., cancer]; 2_ mental health [e.g., depression]; 3_eating disorder; 4_other [i.e. dementia]), *channel* (1_synchronous only; 2_asynchronous only; 3_synchronous and asynchronous), *mentorship* (1_ have professional mentor/facilitator; 2_ no professional mentor/facilitator), *outcome variable* [4] (1_depression; 2_social support; 3_quality of life; 4_self-efficacy; 5_other), *SES* (1_ mixed; 2_ students) being analyzed as categorical moderators respectively. Moreover, *participants' mean age*, *percentage of female participants* (to examine the influence of gender), *evaluation time*, and *group size* were analyzed as continuous moderators. Whether the participants were an at-risk population was not analyzed as a potential moderator considering the lack of variance in the current sample.

Topic. For health topic as a potential moderator, given the significant between-study variance under the fixed-effect model ($Q_{between}$ ($df = 3$) = 26.999, $p < .001$), the moderator analysis was conducted under a mixed-effect model. Under mixed-effect model, the $Q_{between}$ was still significant, $Q_{between}$ ($df = 3$) = 26.997, $p < .001$ with Q_{within} (Q_{within} ($df = 38$) = 55.608, $p < .05$) also significant. Therefore, there were significant mean differences depending on which health topic the interventions were conducted on, but topic does not explain all the variance in this sample. Under the mixed effect model, the weighted mean effect sizes for depression and other mental health issues ($d = .35$, $SE = .05$, $K = 15$, 95% CIs [.25, .45], $p < .001$) and for eating disorders ($d = .72$, $SE = .20$, $K = 3$, 95% CIs [.32, 1.11], $p < .001$) were statistically significant, while the mean effect size of online support groups on chronic diseases ($d = .07$, $SE = .05$, $K = 22$, 95% CIs [.03, .16], $p > .05$) was not significant. For pairwise comparison using Tukey contrasts, the mean effect size of online support group on chronic disease was significantly lower than that on mental health ($p < .001$) or on eating disorder ($p < .01$).

Channel. Channel turned out not to be significant as a moderator in the current sample, given the nonsignificant between-study variance under the fixed-effect ($Q_{between}$ ($df = 2$) = 0.068, $p > .05$). The weighted mean effect sizes of the online support group using synchronous channel only ($d = .21$, $SE = .30$, $K = 3$, 95% CIs [-.38, .80], $p > .05$), using asynchronous channel only ($d = .21$, $SE = .05$, $K = 36$, 95% CIs [.11, .30], $p < .001$), and using both synchronous and asynchronous channels ($d = .20$, $SE = .25$, $K = 3$, 95% CIs [-.29, .70], $p > .05$) were similar, but only the asynchronous-channel support group has a significant mean effect size. The nonsignificant weighted mean effect sizes of online support groups using the other two kinds of channels could be due to the wide range of standard errors, which result from the small sample size.

Mentorship. Whether a professional mentor/facilitator is available for the online support group was not significant in this sample, since the between-study variance was significantly under both the fixed-effect ($Q_{between}$ ($df = 1$) = 0.90, $p > .05$). Although both the weighted mean effect sizes of online support groups with a mentor ($d = .30$ $SE = .07$, $K = 34$, 95% CIs [.17, .44], $p < .001$) and the support groups without a mentor ($d = .13$, $SE = .06$, $K = 74$, 95% CIs [.01, .25], $p < .05$) were statistically significant, the mentored groups do not have a significantly higher weighted mean effect size than the non-mentored group ($p > .05$).

Outcome variable. The nonsignificant between-study variance under the fixed-effect model ($Q_{between}$ ($df = 3$) = 2.87, $p > .05$) indicated that outcome variable does not significantly moderate the effect sizes of the studies in the current study. Specifically, the weighted mean effect sizes for depression, social support, quality of life, and self-efficacy were .19 ($SE = .04$, $K = 19$, 95% CIs [.12, .26], $p < .001$), .19 ($SE = .08$, $K = 7$, 95% CIs

[.03, .36], $p < .05$), .19 ($SE = .06$, $K = 11$, 95% CIs [.08, .31], $p < .01$), .04 ($SE = .09$, $K = 5$, 95% CIs [-.13, .21], $p > .05$), respectively, among which only the mean effect size of self-efficacy was not statistically significant.

Social economic status. Social economic status (SES) turned out to be a significant moderator, given that the between-study variances under both the fixed-effect ($Q_{between}$ ($df = 1$) = 18.95, $p < .001$) and mixed-effect models ($Q_{between}$ ($df = 1$) = 15.37, $p < .001$) were statistically significant. Specifically, both the weighted mean effect sizes of the interventions conducted with general population with mixed SES ($d = .16$, $SE = .04$, $K = 37$, 95% CIs [.09, .24], $p < .001$) and with student sample ($d = .86$, $SE = .18$, $K = 5$, 95% CIs [.51, 1.21], $p < .001$) were statistically significant, with the effect sizes of the online support group with student samples being significantly higher ($p <. 001$).

Participants' mean age. Participants' mean age were significantly moderating the effect sizes of online support groups because the between-study variance was significant under both the fixed-effect model ($Q_{between}$ ($df = 1$) = 20.06, $p < .001$) and the mixed effect models ($Q_{between}$ ($df = 1$) = 18.73, $p < .001$). The slope of the meta-regression showed that the estimated mean effect size decreased by .02 ($SE = .005$, 95% CIs [-.03, -.01], $p < .001$) given one additional year of participants' mean age in the support group. The confidence interval of slope was negative because the point estimate was -.02.

Percentage of female participants. The significant between-study variances under both the fixed-effect ($Q_{between}$ ($df = 1$) = 21.98, $p < .001$) and mixed-effect models ($Q_{between}$ ($df = 1$) = 21.97, $p < .001$) indicated that the gender was a significant moderator for interactive health interventions. The estimated intercept and slope were .94 ($SE = .17$,

$K = 42$, 95% CIs [.61, 1.26], $p < .001$) and -.01 ($SE = .002$, $K = 42$, 95% CIs [-.01, -.005], $p < .01$), which indicated that the mean effect size for the intervention with no female participant was significant, but will decrease by .01 given an additional one percentage of female participants in the online support group.

Evaluation time. When the post-test evaluation was conducted it turned out not to be significant as another continuous moderator, given the nonsignificant between-study variance under the fixed-effect ($Q_{between}$ ($df = 1$) = 1.05, $p > .05$). The intercept was statistically significant ($d = .21$, $SE = .05$, $K = 108$, 95% CIs [.17, .37], $p < .001$), but the slope was not ($p > .05$).

Group size. With depression as the outcome variable, the group size was found to be a significant moderator given the significant between-study variances under both the fixed-effect ($Q_{between}$ ($df = 1$) = 15.57, $p < .001$) and mixed-effect models ($Q_{between}$ ($df = 1$) = 15.57, $p < .001$). The estimated intercept and slope was .25 ($SE = .04$, $K = 33$, 95% CIs [.19, .33], $p < .001$) and -.001 ($SE = .0002$, $K = 33$, 95% CIs [-.001, -.0005], $p < .001$). Although the intercept does not contain much meaningful information, the result of slope indicated that the mean effect size for the intervention in improving depression will decrease by .001 given an additional one participant in the online support group. Figure 6 shows the plot of the relationship between group size and effect sizes for depression. When fitting a linear meta-regression model, group size was not a significant moderator, as the between-study variances was significant only under the fixed-effect model ($Q_{between}$ ($df = 1$) = 3.90, $p < .05$) but not under mixed-effect model ($Q_{between}$ ($df = 1$) = 1.32, $p > .05$). In addition, group size turned out to be not significant ($p > .05$) under either quadratic (F (2, 12) = 2.15, $p = .16$, adjusted $R^2 = .1415$) or cubic model (F (3, 11) = 2.93, *p* = .08, adjusted R^2 = .2922). Although an additional 15% of variance in the effect sizes was explained by the cubic model compared to the quadratic model, the model comparison result suggests an acceptance of the null hypothesis that there was no significant improvement of the model (*p* = .08). Figure 7 shows the plot of the relationships between group size and effect sizes for social support.

Study 3

Study Description

A total of 23 studies were included in Study 3 meta-analysis. The studies analyzed, sample size, dependent variable constructs, participants' mean age, and effect sizes (*d*) employed were reported in Table 9. For the experimental studies that have multiple effect sizes produced by multiple conditions, they were treated as separate studies by following Schmidt and Hunter's (1999) approach. Therefore, 108 effect sizes were analyzed. Among these 23 articles, which were published during 2003 to 2014, eleven appeared in the *Journal of Medical Internet Research* (i.e., Camerini & Schulz, 2012; Danaher et al., 2013; Jones et al., 2014; Linke, Murray, Butler, &Wallace, 2007; Richardson et al., 2013; Riva et al., 2014; Robinson et al., 2014; Salazar, Vivolo-Kantor, Hardin, & Berkowitz, 2014; Schaub, Sullivan, Haug, & Stark, 2012; Solomon, Wagner, & Goes, 2012; Webster, Li, Sullivan, Jayne, Su, & Neal, 2010), two in the *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine* (i.e., De Bourdeaudhuij, Stevens, Vandelanotte, & Brug, 2007; Napolitano et al., 2003), one in the *Journal of the National Cancer Institute* (i.e., An et al.,2013), one in the *Alcoholism, Clinical and Experimental Research* (i.e., Delrahim-Howlett et al., 2011), one in the *Health Education Research* (i.e., Hasson, Brown, & Hasson, 2010), one in the *Psychology and Health* (i.e., Hurling, Fairley, & Dias, 2006), one in the *Journal of Pediatric Psychology* (i.e., Law, Murphy, & Palermo, 2012), one in the *Applied Nursing Research* (i.e., Logston et al., 2013), one in *International Journal of Audiology* (Martin, Griest, Sobel, & Howarth, 2013), one in the *British Journal of Health Psychology* (i.e., Morrison, Moss-Morris, Michie, & Yardley, 2014), one in the *International Journal of Nursing Practice* (i.e., Moussa, Sherrod, & Choi, 2013), and one in the *Children's Health Care* (i.e., Ritterband et al., 2013).

Among these studies, ten studies focused on populations at risk (An et al., 2013; Camerini & Schulz, 2012; Danaher et al., 2013; Delrahim-Howlett et al., 2011; Jones et al., 2014; Law et al., 2012; Logsdon et al., 2013; Moussa et al., 2013; Robinson et al., 2014; Schaub et al., 2012), while other 13 studies focused on healthy populations. Student samples were used in three studies (Jones et al., 2014; Martin et al., 2013; Salazar et al., 2014), while the other studies examined adults. Except for Salazar and his colleagues' study (2014), which only included male college students, and Linke and his colleagues' study (2007), which only included male adults, most studies included both male and female participants. In total, 7,065 (N = 7,065) participants were included in the meta-analysis.

Publication Bias

Publication bias may exist when the publication status depends on the statistical significance of study results (Sutton, 2009). There are multiple ways to check for a potential publication bias problem. First, a funnel plot can be used for examination of whether effect sizes from smaller studies show more variability than those from larger studies. As shown in Figure 8, the funnel plot of effect sizes seems to be generally symmetric, which provides evidence for the absence of publication bias. Further, the Egger's regression test for funnel plot asymmetry was not statistically significant (z = -.37, p = 0.71), indicating that publication bias probably does not exist in this sample. Moreover, Rosenthal's Fail-safe N was 36,165, which is larger than the tolerance level ($5k + 10 = 550$), and further confirmed the absence of publication bias.

Overall Analysis

Q statistics were applied to examine whether the effect sizes were from the same population. Because Q_{total} was significant (Q_{total} (df = 107) = 1283.84, p < .001), the effect sizes were not homogeneous, and mean effect size under the random-effect model was estimated by Restricted Maximum Likelihood Estimation (REML) method. Under the REML model, the sample weighted mean for standardized mean difference was 0.427 (N = 7,065, K = 108, 95% CIs [.34, .51]), which was regarded as medium effect size (Cohen, 1988) and statistically significance (p < .01). In other words, there were statistically significant mean differences between the treatment and control groups according to the overall analysis. Moreover, I^2, an index representing the ratio of true heterogeneity to total variance across observed effect sizes, is 92.21%, which showed large between-study variance in this case. Similarly, Birge's ratio, another index to quantify the magnitude of heterogeneity, was computed as Q/df = 1283.84/ 107 = 12.00. Since Birge's ratio was much larger than one (which is ratio when all the variance comes from sampling error), we can conclude that the between-study heterogeneity was large in this study. Sampling error variance (S_e^2 = 0.0293) only accounted for 16.57% of the total variance (S^2 = 0.1768), indicating the presence of moderator(s). Therefore, the hypothesized categorical and continuous moderators were analyzed.

Moderator Analysis

Given the significant *Q* statistics, which indicated heterogeneity of the effect sizes across these 23 studies with 108 effect sizes, moderator analyses were conducted with *publication type* (1_journal article; 2_ conference proceeding), *topic* (1_tobacco use; 2_ substance abuse [e.g., drinking or cocaine use]; 3_mental health; 4_nutrition, physical activity, and overweight [5]; 5_ health communication and health information technology; 6_ chronic diseases; 7_other [i.e., injury and violence prevention, hearing]), *subgroup* (1_normal adults; 2_people at risk), *intervention design* (1_RCT; 2_pre and post repeated design), *control group design* (1_ static version; 2_ no intervention), *intervention frequency* (1_once; 2_ weekly; 3_less than once a week), *outcome variable* (1_affective [e.g., attitude]; 2_cognitive [e.g., self-efficacy, awareness]; 3_health behavioral and intention; 4_health outcomes (health condition and other criteria); 5_engagement with the program), *outcome measure* (1_nominal; 2_interval [e.g., Likert scale]; 3_Ratio), *SES* (1_ middle; 2_ low; 3_students) being analyzed as categorical moderators respectively. Moreover, *publication year*, *participants' mean age*, *percentage of female participants* (to examine the influence of gender), and the *length of the intervention* were analyzed as continuous moderators.

Publication type. For publication type as a potential moderator, given the significant between-study variance under the fixed-effect model ($Q_{between}$ (df =1) = 22.69, p < .001), the moderator analysis was conducted under a mixed-effect model. However, under mixed-effect model, the $Q_{between}$ was not significant, $Q_{between}$ (df = 1) = 1.00, p = .32. Therefore, the effect sizes of journal publications and conference proceedings do not significantly differ from each other.

Topic. For health topic as a potential moderator, given the significant between-study variance under the fixed-effect model ($Q_{between}$ (df = 6) = 634.36, $p < .001$), the moderator analysis was conducted under a mixed-effect model. Under mixed-effect model, the $Q_{between}$ was still significant, $Q_{between}$ (df = 6) = 49.76, $p < .001$. Therefore, there were significant mean differences depending on which health topic the interventions were conducted on. Under the mixed effect model, the weighted mean effect sizes for tobacco use (d = .20, SE = .06, K = 11, 95% CIs [.08, .32], $p < .01$), for substance abuse (d = .46, SE = .09, K = 17, 95% CIs [.27, .64], $p < .001$), for mental health (d = .90, SE = .14, K = 19, 95% CIs [.62, 1.18], $p < .001$), for nutrition, physical activity, and overweight (d = .43, SE = .06, K = 24, 95% CIs [.31, .56], $p < .001$), for chronic diseases (d = .19, SE = .06, K = 18, 95% CIs [.08, .30], $p < .001$) were statistically significant. However, the mean effect size of interventions on health communication and health information technology was not significant (d = .09, SE = .07, K = 14, 95% CIs [-.04, .23], $p > .05$). For pairwise comparison using Tukey contrasts, the mean effect size of interactive interventions on mental health was significantly higher than the mean effect sizes of interventions on all the other topics ($p < .001$). In addition, the mean effect size of interventions health communication and health information technology was significantly lower than those on substance use and nutrition ($p < .05$).

Subgroup. Subgroup turned out to be a significant moderator, given the significant between-study variance under both the fixed-effect ($Q_{between}$ (df = 1) = 46.75, $p < .001$) and mixed-effect models ($Q_{between}$ (df = 1) = 7.34, $p < .01$). Both the weighted mean effect sizes of the interventions conducted with healthy adults (d = .30, SE = .05, K = 53, 95% CIs [.22, .39], $p < .001$) and population at risk (d = .54, SE = .07, K = 55, 95%

CIs [.40, .69], $p < .001$) were statistically significant, with the effect sizes of the interventions on population at risk being significantly higher ($p <. 01$).

Intervention design. Intervention design was another significant moderator, since the between-study variance was significantly under both the fixed-effect ($Q_{between}$ ($df = 1$) = 190.14, $p < .001$) and mixed effect models ($Q_{between}$ ($df = 1$) = 43.88, $p < .001$). Specifically, the weighted mean effect size of pre-post repeated-measures designs, which was .77 ($SE = .09$, $K = 34$, 95% CIs [.59, .95], $p < .001$), was significantly higher than that of the randomized control trials ($d = .22$, $SE = .03$, $K = 74$, 95% CIs [.17, .27], $p < .001$) at .001 level ($z = 6.62$).

Control group design. Whether the control groups in the interventions used a static version of design or used no design was another significant moderator, since the between-study variance was significantly under both the fixed-effect ($Q_{between}$ ($df = 1$) = 170.33, $p < .001$) and mixed effect models ($Q_{between}$ ($df = 1$) = 32.18, $p < .001$). The weighted mean effect size for the control groups conducting no intervention ($d = .65$, $SE = .07$, $K = 53$, 95% CIs [.51, .79], $p < .001$) was significantly higher than the effect size for the control groups using a static version of intervention ($d = .20$, $SE = .03$, $K = 55$, 95% CIs [.14, .26], $p < .001$) at .001 level ($z = 5. 66$).

Intervention frequency. The frequency of interactive interventions was also a significant moderator, given the significant between-study variance under both the fixed-effect ($Q_{between}$ ($df = 2$) = 462.69, $p < .001$) and mixed effect models ($Q_{between}$ ($df = 1$) = 44.03, $p < .001$). The weighted mean effect sizes were .12 ($SE = .03$, $K = 39$, 95% CIs [.06, .19], $p < .001$), .64 ($SE = .06$, $K = 63$, 95% CIs [.52, .76], $p < .001$), and .29 ($SE = .17$, $K = 6$, 95% CI [-.05, .63], $p > .05$) for interventions conducted only once, every week, and less than once a week respectively. For the significant mean effect sizes, the effect of weekly interventions was significantly higher than that of the one-shot interventions ($p < .001$, $z = 6.62$).

Outcome variable. The significant between-study variance under both the fixed-effect ($Q_{between}$ ($df = 4$) = 513.33, $p < .001$) and mixed effect models ($Q_{between}$ ($df = 4$) = 17.85, $p < .001$) indicated that outcome variable significantly moderates the effect sizes of the studies in the current study. Specifically, the weighted mean effect sizes for affective variables, cognitive variables, behavioral intentions, health conditions, and engagement were .21 (SE = .06, K = 13, 95% CIs [.09, .32], $p < .001$), .48 (SE = .09, K = 22, 95% CIs [.31, .65], $p < .001$), .29 (SE = .06, K = 42, 95% CIs [.18, .41], $p < .001$), .69 (SE = .12, K = 26, 95% CIs [.45, .92], $p < .001$), .28 (SE = .07, K = 5, 95% CIs [.13, .42], $p < .001$) respectively, all of which were statistically significant. For pairwise comparison, the mean effect size of health conditions was significantly higher than that of affective outcomes ($p < .01$, $z = 2.88$), behavioral intentions ($p < .001$, $z = 3.94$), and engagement ($p < .05$, $z = 2.26$).

Outcome measure. For outcome measure as a potential moderator, given the significant between-study variance under the fixed-effect model ($Q_{between}$ ($df = 2$) = 352.51, $p < .001$), the moderator analysis was conducted under a mixed-effect model. Under mixed-effect model, the $Q_{between}$ was also significant, $Q_{between}$ ($df = 2$) = 13.80, $p < .001$. Therefore, measure was a significant moderator of the effect sizes. Specifically, studies with outcome variables using interval measures have significantly higher effect sizes (d = .57, SE = .07, K = 57, 95% CIs [.44, .72], $p < .001$) than those with outcome variables using nominal measures (d = .28, SE = .08, K = 21, 95% CIs [.12, .45], $p < .001$)

and those with outcome variables using ratio measures (d = .24, SE = .04, K = 30, 95% CIs [.15, .33], p < .001) at .01 (z = 2.75) and .001 level (z = 3.30) respectively.

Social economic status. Under fixed-effects model, SES as a moderator was not significant $Q_{between}$ (df = 2) = 5.91, p > .05. Therefore, no follow-up analysis was needed.

Publication year. Regarding publication year as a potential moderator, both the between-study variance ($Q_{between}$ (df = 1) = 157.40, p < .001) was statistically significant under the fixed-effect model, which indicates that topic could potentially be a moderator. Therefore, mixed effect model was used for moderator analysis. However, under the mixed-effects model, the moderator test was no longer significant ($Q_{between}$ (df = 1) = .78, p = .38). Therefore, publication year was not a continuous moderator.

Participants' mean age. Participants' mean age were not significantly moderating the effect sizes of interactive health interventions because the between-study variance was significant under the fixed-effect model ($Q_{between}$ (df = 1) = 36.85, p < .001), but not under the mixed effect model ($Q_{between}$ (df = 1) = .06, p = .81).

Percentage of female participants. The significant between-study variances under both the fixed-effect ($Q_{between}$ (df = 1) = 83.52, p < .001) and mixed-effect models ($Q_{between}$ (df = 1) = 10.45, p < .01) indicated that the gender was a significant moderator for interactive health interventions. The estimated intercept and slope was .09 (SE = .12, K = 105, 95% CIs [-.14, .31], p > .05) and .005 (SE = .002, K = 105, 95% CIs [.002, .008], p < .01). Although the nonsignificant intercept indicates that the mean effect size for the intervention with no female participant was not significant, the significant slope shows that the estimated mean effect size increases by .005 given an additional one percentage of female participants in the intervention.

Length of the intervention. The length of the intervention was another significant continuous moderator, given the significant between-study variance under both the fixed-effect ($Q_{between}$ ($df = 1$) = 237.39, $p < .001$) and mixed-effect models ($Q_{between}$ ($df = 1$) = 23.25, $p < .001$). The intercept and the slope was .27 ($SE = .05$, $K = 108$, 95% CIs [.17, .37], $p < .001$) and .02 ($SE = .004$, $K = 108$, 95% CIs [.013, .030], $p < .001$) respectively, both of which were significant. The mean effect size for the one-shot interventions was significant, but increased by .02 given an additional week of the intervention duration.

In the next chapters, the findings of the three meta-analyses will be discussed. Additionally, the Discussion chapter will also address the implications and limitations of the current study. Finally, direction for future research will be described, followed by a conclusion of the study.

CHAPTER 5

DISCUSSION

In this chapter, findings of the overall effects and the moderator analyses in Study 1, Study 2, and Study 3 will be discussed. In addition, limitations of the current research will be noted, including suggestions for a future research agenda. Specific implications of the findings relating to these three meta-analyses in computer-mediated health communication (CMHC) will also be explored.

Study 1

Overall Effects

Along with computer-mediated communication being more widely applied to health communication, one major application is conducting health interventions on the basis of social media. Despite social media's potential to enhance users' self-efficacy, perceived social support, and behavioral capability according to social cognitive theory (Bandura, 1986; Valle et al., 2013), whether it was effective in health intervention and the magnitude of the effect remains unclear. The results of the current meta-analyses indicated that social-media-based health interventions were effective on average, but to a limited extent. The random-effects weighted mean correlation was .17 and statistically significant ($p < .01$). However, according to Cohen's (1988) convention for small (d = 0.20), medium (d = 0.50), and large (d = 0.80) effects, the effect size was small. One possible reason for the small mean effect was that several effect sizes were negative, indicating that after the health intervention, the outcomes of the treatment group were in the opposite direction of the researchers' hypotheses. This could be due to a couple of possible reasons, such as the methods used in their intervention, the characteristics of the subgroup involved in the study, the imperfect outcome measurement, or other confounding variables that should have been controlled.

Moderator Analysis

In this study, it was found that whether researchers used continuous scales with multiple items or categorical measures significantly moderated the effect sizes. Specifically, categorically measured outcome variables turned out to have significantly higher effect sizes (d = .50, SE = .26, K = 6, 95% CIs [-.013, .014]) than those with outcome variables being continuously measured (d = .081, SE = .06, K = 28, 95% CIs [-.035, .197]) (p < .05). This finding may be counterintuitive, but important for health education and interventions by providing guidance for the intervention evaluation. One possible explanation could be that the continuous measures of the outcome variables in the meta-analyzed studies were not ideal. Among the meta-analyzed articles, only four studies (i.e., Livingston et al., 2013, 2014; Napolitano et al., 2013; Valle et al., 2015) reported scale reliabilities or results of confirmatory factor analysis (CFA), while the reliability and validity of measures in other studies were unknown. In this case, the continuous measures of outcome variables could produce a wide range of measurement error that cancel out the effect sizes. Although a closer examination of the outcome variables at the measurement level is needed to identify the exact reasons for such differences, this significant moderating effect can inform health communication scholars of the importance in choosing intervention measures and the possible differences resulting from measures.

The second interesting finding of the moderator analysis was the reducing long-term effect of the health intervention. Since the intercept of the moderator analysis was significant (d = .34, p < .05), the intervention was effective right after the study (at zero time point). However, it was found that for another additional week, the effect decreased by .01 (p < .05). The finding provided noteworthy evidence that the social-media-based health interventions conducted so far have limited long-term effect. In other words, the cognitive, attitudinal, or behavioral changes resulting from the intervention may not be sustainable, and might disappear after a certain amount of time. Possible reasons for decreasing effect sizes over time could result from loss of participant engagement in the social media intervention, and less frequently logging into their accounts. These results suggest health communication scholars need to cautiously draw conclusions relating to the effectiveness of social-media-based interventions if studies are cross-sectional designs, and retest the effects in a longitudinal manner. This has been a major challenge confronted by health communication researchers that needs additional focus on the effect of sustainable long-term health intervention.

The primary limitation of the current study was the small sample size. Since social media has recently been applied to health interventions, and intervention and evaluation usually take time to conduct, not many published articles describing their interventions were available. In this regard, the small sample size limited the statistical power and consequently the opportunity to discover a significant moderator. Given the significance of the topic, the study contributed a timely systematic review and provided guidance for health communication scholars and professionals.

Study 2

Overall Effects

Consistent with previous studies (e.g., Rains & Young, 2009; Walther & Boyd, 2002; Wright & Bell, 2003), CMSGs were found to have a positive effect on health outcomes among participants in general according to the studies published after 2009. This positive effect could be explained by both the buffering model (Cohen & Wills, 1985) suggesting that social support helps in reducing stress and the main effect model (Cohen & Wills, 1985) maintaining that an increased social support will result in an increase in well-being. However, the effects of online support groups were mixed with a wide range of negative effect sizes (e.g., Salzer et al., 2010) to 1.33 (Ellis et al., 2011). The significance of the CMGs and the mixture of empirical results indicate the necessity for a systematic review. Moreover, Rains and Young's study (2009), group size was found to be a non-significant moderator of social support. Rains and Young posited in their discussion that the relationship could be curvilinear, but this was not tested. Therefore, a retest of the moderating effect of group size in perceived social support and depression with a larger sample size by fitting a nonlinear model of group size and perceived social support is warranted.

Based on 15 studies with 42 effect sizes, the current meta-analytic review indicated that on average, the random-effects standardized mean difference was .21 and statistically significant ($p < .001$). According to Cohen's convention for small ($d = 0.20$), medium ($d = 0.50$), and large ($d = 0.80$) effects, health interventions using online support group on average have a small but significant effect. In other words, participants in the online support group will have significantly improved health outcomes after the support group intervention compared to the baseline, which was consistent with the findings of previous meta-analytic review (Rains & Young, 2009). Besides the point estimate analysis, which provides evidence for the general effectiveness of an online support group, the large variance in the outcome variables was noteworthy. This makes an analysis for moderators imperative.

Moderator Analysis

In this study, a series of interesting moderating effects were found, which could potentially provide importance guidance for future health interventions using CMSGs. The first important finding was CMSGs have a significantly higher effect size on addressing mental health and eating disorders than addressing chronic disease. A possible explanation could be due to the stigmatization of depression (Griffiths, Christensen, Jorm, Evans, & Groves, 2004) and eating disorder (Mond, Robertson-Smith, & Vetere, 2006). There was research showing that people tend to have significantly more stigmatized attitudes towards individuals with eating disorders than attitudes towards depressed individuals (Roehrig & McLean, 2010). Such stigmatization could prevent individuals with eating disorders or depression from seeking social support in a face-to-face context due to embarrassment or lack of privacy. However, individuals with embarrassing or stigmatizing conditions may find that the relative anonymity of CMSGs provided them with more freedom and comfort to openly discuss their concerns (Andersson, Bergstrom, Hollandare, Carlbring, Kaldo, & Ekselius, 2005). Therefore, the advantages of CMSGs in improving health outcomes of participants with depression or eating disorders could be more salient than the advantages in improving health outcomes of participants with cancer, which is less stigmatized.

Another interesting finding came from the significantly higher mean effect size obtained by studies using student samples than the mean effect size with adults of mixed social economic status. This difference was consistent with the previous study that similarity between social group members could generate more empathy, which led to more supportive exchanges (Wellman & Wortley, 1990). Since perceived similarity was more likely to generate positive impressions in the computer-mediated context (Yang & Li, 2013), students in a CMSG could feel more comfortable using self-disclosure and social support seeking with other group members who were also students and have similar experiences. In comparison, it may be more difficult or take longer time for adult participants with mixed SESs to establish mutual trust and conduct supportive exchanges.

Gender was found to be another significant moderator in the CMSGs, which could be explained by the differences in socialization and social support (Shumaker & Hill, 1991). Previous research found that females were more likely to have more confidants throughout their life span than males, who often refer to spouses as their only confidants (Flaherty & Rickman, 1989; Lowenthal & Haven, 1968; Power & Bultena, 1976). Men were found to be much more likely than women to perceive that they have never had any confidant outside the family (Powers & Bultena, 1976). In addition, the size of group networks for men shrink at a faster rate with aging than size of networks for women (Depner & Ingersoll-Dayton, 1988; Field & Minkler, 1988). Considering the lack of social support in the face-to-face context for men in general compared to women, computer-mediated support provided by online support groups could be more necessary and helpful for male participants than for female participants. The difference might be explained based on men and women's characteristics: femininity was found to be warm, supportive, compassionate and emotionally expressive, while masculinity underemphasize social relationships and focus on independence, competitiveness and self-reliance (Bakan, 1966; Deaux & LaFrance, 1998). Therefore, female participants were better prepared to seek, receive, and provide support in their daily life than their male counterparts, which may decrease female's need for social support in the computer-mediated context.

Different from Rains and Young's (2009) finding that group size was significantly moderating the effect sizes of depression, a negative relationship between group size and depression was found in the current sample size. One possible reason for the discrepancy could be due to the increased statistical power with a larger sample size (Cohen, 1977). This significant moderating effect could also be attributed to the stigmatization of depression (Andersson et al., 2005), since many individuals with depression regard this health problem as personal and confidential (Gould, Munfakh, Lubell, Kleinman, & Parker, 2002) and were unwilling to share this problem with many people. Therefore, a smaller social support group might provide participants (experiencing depression) with a higher level of comfort to seek support and confide in others. However, due to the insufficient empirical studies conducted with small online support groups, the optimal number of CMSG remains unclear and deserves further investigation. Regarding the relationship between group size and social support, the marginally significant cubic model and the increased adjusted *R* square of cubic model compared to the linear or quadratic model indicated promise of the cubic relationship, but a definite conclusion was not able to be made at this point.

Besides the significant findings of the moderator analyses, several nonsignificant findings also deserve attentions. First, although the absence of a trained facilitator has been found to be associated with greater levels of depression and lower quality of life (Lieberman & Goldstein, 2006), mentorship was found to be nonsignificant in the current sample. One explanation could be that mentors were trained in a diverse way and the effectiveness of the presence of a mentor could vary wildly. Therefore, a closer examination of mentors' characteristics, roles and effects in CMSGs is needed. Second, no significant difference was found for participants of different ages although young people, such as "Generation Y" or "Net Generation" (Behrstock-Sherratt & Coggashall, 2010), were considered to be engaged in computer-mediated communication more frequently than older generations. These findings provided some confidence for the potential generalizability of CMSGs to all age groups. Third, although previous literature (e.g., Kim, 2013) indicated that it may take some time to build and form a bond with other peers, no significant time effect was found in the current sample. Operationalization could be a possible reason. Since many studies did not make a clear distinction between the end of the support group intervention and the time of the post-test, it could be possible that the positive effect gained by the lasting online support group was offset as time went by. However, given the comparatively small sample size, all the nonsignificant results should be considered with caution and a reanalysis of the nonsignificant moderators with a larger sample size is warranted.

CMSGs, varying in terms of both design-related factors (e.g., group size, length of intervention) and participants' characteristics (e.g., age, SES, gender), could result in different effects on participants' outcome variables. This meta-analytic review, based on a previous review (Rains & Young, 2009) and incorporating additional 15 recently published studies provided more guidance for future CMSG design and points to a new direction for scholarly research in online support groups.

Study 3

Overall Effects

Based on the social comparison theory (Festinger, 1954), the interactive features have been increasingly applied to health interventions because of their features of computer-mediated communication that facilitate message delivery such as tailored messages, instance feedback and trackable progress (Meischke, Lozano, Zhou, Garrison, & Christakis, 2011). However, the effects of using interactive interventions were mixed, with a wide range from negative effect sizes (e.g., Morrison et al., 2014) to 2.10 (Danaher et al., 2013). The significance of the topic and the mixture of empirical results indicated the necessity for a systematic review. According to Webster and his colleagues (2010), many websites provide interactive, tailored advice in an attempt to help bridge the evidence-practice gap, yet little evidence was available that provision of such a tool was effective in changing practice.

The current meta-analytic review of 23 studies with 108 effect sizes indicated that on average, the random-effects standardized mean difference is 0.427 and statistically significant ($p < .01$). According to Cohen's (1988) convention for small ($d = 0.20$), medium ($d = 0.50$), and large ($d = 0.80$) effects, health interventions with interactive features on average have a medium effect. Additionally, even though the control group participants used static version of health intervention, effect of the interactive version of intervention was still significantly better ($d = .20$, $SE = .03$, $K = 55$, 95% CIs [.14, .26], p

< .001). Besides the point estimate analysis that provided evidence for the general effectiveness of interactive interventions, the large variance in the effectiveness was noteworthy and analysis for moderators was imperative.

Moderator Analysis

In this study, a series of interesting moderating effects were found, which could potentially provide importance guidance for future health interventions using interactive features. The first important finding was interactive interventions have a significantly higher effect size on addressing mental health issues than the other topics. One possible reason for this difference is the stigmatization of mental health (Andersson et al., 2005; Griffiths et al., 2004) where the patients might suffer from social isolation and hesitance to socialize in a face-to-face setting. Therefore, the web-based interventions with interactive features provide them with a virtual venue to benefit from interactivity anonymously and with ease. The other reason could be attributed to the cognitive benefits of interactive media as cognitive behavioral therapy (Schwan & Riempp, 2004). Unlike traditional media, which can only address a general audience and was almost impossible to take into account individual differences, the interactive interventions provided tailored feedback for each individual in a timely manner. Such features that enabled the user to adapt the intervention to her or his individual cognitive needs, according to Schwan and Riempp (2004), balances the interplay of users' internal (mental) and external (media directed) activities. The users modifying external information was referred to as "epistemic action" (Kirsh & Maglio, 1994, p.513), which facilitated and simplified the mental process. Given the cognitive benefits of interactive media and the "illusion" in mental health patients' cognition (Taylor & Brown, 1988), interventions could possibly work better for those internal health problems, such as mental health.

Another noteworthy finding was the weighted mean effect size being significantly higher for the health outcome variables than affective and cognitive variables. One possible explanation could be that health outcome was a terminal variable, the change of which may be more visible than proximal or distal predictors (e.g., affect and cognition). Specifically, theories from cognitive perspectives (e.g., theory of planned behavior) suggest that cognitive beliefs serving as proximal factors directly influence behavioral outcomes, while affective components serve as distal or confounding variables. By contrast, risk-as-feelings hypothesis argues that affect produces a direct effect on behavioral measures and there is a reciprocal relation between cognition and affect (Loewenstein, Weber, Hsee, & Welch, 2001).

Furthermore, compared to the healthy population, the participants who were at risk of certain health issues tend to benefit more from interactive design. This significant difference was understandable because participants at risk can be made aware of their risk after health interventions, and make subsequent changes to reduce that risk (e.g., Floyd et al., 2007). Such cognitive and behavioral changes can be more manifested than that of the general population who has less room to make positive changes compared to the at-risk counterparts. In addition, the interactive design was also found to have a better effect on female participants. One possible reason for this significant moderating effect could be due to the gender difference regarding health issues. Previous research found that females showed higher participation rates in health interventions (Hasson et al., 2010; Linke et al., 2007) and were more concerned about health than males (Chrisler, 2001). Another possible reason could be due to the general testing effect that females were less engaged with interactive features (e.g., video games) than males who were more use to this interactivity.

Methodologically, the findings in this study indicated that the length of intervention was found as a significant moderator, which lends support to the argument that communication is a *process* by nature (Stephenson, Holbert, & Zimmerman, 2006). In line with this argument, weekly interventions were found to be more effective than cross-sectional interventions, which were consistent with health communication methodologists' suggestion that longitudinal designs were needed to observe subsequent changes in health (Stephenson, Southwell, & Yzer, 2011). Given the limitation of cross-sectional designs in detecting the trajectory of change and effect, these results added further evidence of longitudinal intervention benefits and the need for statistical analysis of time-based modeling.

In addition to significant findings of the moderator analyses, several non-significant findings also deserve attention. First, the non-significant moderating effect of publication type provided further evidence for the absence of publication bias, since studies published in journals do not show significantly higher effect sizes than other studies published in conference proceedings. Second, although previous literature (e.g., Ritterband et al., 2006) indicated that interactive features could probably work better for kids than adults, especially for motivation, no age difference was found in the effects of these 23 studies. Similarly, no significant difference was found for participants of different SES although interactive intervention might attract older and more educated participants in cocaine consumption (Schaub, Sullivan, Haug, & Stark, 2012). Such findings provided confidence for the potential generalizability of interactive interventions of all age and SES groups.

Interactivity, an attribute of technology (Sundar, 2004), can be defined as “the extent to which users can participate in modifying the form and content of a mediated environment in real time” (Steuer, 1992, p.84). In this sense, traditional media has limitations in terms of interactivity, while new technologies (e.g., the Internet) share a high level of interactivity. This perspective, known as functional interactivity, offers a theoretically robust way to operationalize an eHealth intervention in terms of its enabling functions (Camerini & Schulz, 2012). Such functional interactivity in eHealth interventions was found particularly effective to address mental health issues in improving the health outcomes, when the interventions were conducted in a longitudinal manner. The results of the overall and moderator analyses obtained in the current study are crucial in informing future research and practice, as well as suggesting directions for web-based interactive health intervention.

Limitations

There are topical and methodological limitations related to the current research project that should be noted. One shared topical limitation for these three meta-analyses was the comparatively small sample sizes, which ranged from 13 to 23. This shortage of primary computer-mediated health interventions could be attributed to several reasons. First, the potential of social-media-based health interventions, online support groups, and online health interventions with interactive features has not drawn wide attention from health communication scholars until recent years. Second, among the scholars who were interested in applying new technologies to health interventions, only a small proportion of them have the financial and technological resources to design and evaluate these types of interventions. Lastly, it usually takes several years for researchers to design, conduct, evaluate, report interventions, and publish their work.

Besides the topic-wise limitations for each of the three studies, the methodological limitations of meta-analyses in general should also be noted. First and foremost, meta-analysis is susceptible to the "apples and oranges" critique concerning the comparability of studies (Borenstein et al., 2009, p. 379). Comparability refers to all of the studies included in one meta-analysis that should examine the same constructs or relationships. The second limitation of meta-analysis is the "garbage in, garbage out" problem (Borenstein et al., 2009, p. 380). Studies included in one meta-analysis differ in quality. Besides unpublished works (e.g., conference paper, thesis, dissertation) whose quality may not have been rigorously evaluated, published studies were not necessarily always high-quality. The fundamental errors in the empirical studies cannot be corrected in meta-analysis and will contaminate the final results. Third, meta-analysis is susceptible to publication/selection bias, which results from the "file drawer problem." Generally speaking, since journals give preference to significant results, some negative and null finding studies were not reported and therefore unavailable (Dickersin, Chan, Chalmersx, Sacks, & Smith, 1987). The danger of including only studies with significant results is that it biases the meta-analytic reviews.

Future Research Agenda

Given the promising field of computer-mediated health communication, the research agenda of communication scholars should include the following aspects. First, researchers need to test the efficacy of applying CMC to health interventions and campaigns, especially in the emerging areas such as social media (Taubenheim, Long, Wayman, Temple, McDonough, & Duncan, 2012) and smart phone apps (Abroms, Padmanabhan, & Evans, 2012). Second, researchers need to contribute to the knowledge about how certain features of CMHC, such as interactivity and tailoring, can improve the efficacy of health interventions (Buller & Floyd, 2012; Noar & Harrington, 2012), and what and how variables moderate the efficacy. Third, with more studies testing the efficacy of computer-mediated health interventions, meta-analytic studies, an underused tool in the communication discipline compared to other health-related areas (Hale & Dillard, 1991), are needed to synthesize the effects and examine both the overall effects and moderating variables (Head, Noar, Iannarino, & Harrington, 2013; Noar, Benac, & Harris, 2007). Fourth, health communication scholars need to take a dissemination perspective when examining the efficacy of CMHC, because the ultimate goal of health communication research is to translate the results into practice. Fifth, in terms of the online health information seeking, communication researchers need to investigate how people seek and internalize online health information, and how heuristic cues given by technological affordances influence their perception. Sixth, since most health theories and models (e.g., health belief model, theory of reasoned action, theory of planned behaviors), has long been criticized as being “Westernized” and lacking the applicability to other cultures (Airhihenbuwa & Obregon, 2000), a multicultural perspective is needed for communication research to examine the efficacy of CMC in health communication, and extend the health communication theories in online environment to non-Western cultures. Seventh, despite the advantages of meta-analytical reviews, future research is encouraged to look at qualitative studies such as in-depth interviews or focus groups, and examine whether the results of the these studies align with those of the meta-analytical reviews. By comparing the results of qualitative and quantitative studies, researchers would have a better understanding and more multi-perspective of CMHC. Finally, longitudinal studies are imperative in health communication where scholars mainly focus on cross-sectional research. Despite the merits of cross-sectional studies, one major limitation is the unknown trajectory of change. Thus, it is limiting to draw conclusions on the effectiveness of a health intervention based on a one-time pretest and posttest given the possibility of short-term and lagging effects. This gap needs to be addressed through grant-funded longitudinal health intervention to provide a comprehensive picture of health education and behaviors.

Implications for CMHC

The findings of this research have several important implications contributing to a better understanding of computer-mediated health communication (CMHC). First, by summarizing a body of research using meta-analytical review of three CMHC topics – social-media-based health interventions, online support groups, online health intervention with interactivity – current research reconciled the mixed findings of these three subareas (Hedges & Olkin, 1985; Hunter et al., 1982). This also addressed the call for more meta-analytical studies in health communication where this type of analysis had been underused (Hale & Dillard, 1991; Noar, 2006). Second, instead of focusing on individual studies, the current study addressed broader questions found in CMHC. Since the mean effect sizes for the three studies were all statistically significant, it provided evidence for the general effectiveness of applying emerging information and communication technology to improve public health (Eng, 2001). This finding is consistent with previous research that computer-mediated communication is becoming an important part of the strategies for health education and health behavior (Noar & Harrington, 2012), and support scholars and professionals dedicated to computer-mediated health communication. Third, this study identified the differences regarding effectiveness of online health interventions across studies. By synthesizing a number of empirical studies evaluating online health interventions of different designs and implementations, the findings of moderator analyses in the current study extended previous reviews of literature (Lustria et al., 2007). This was accomplished by identifying the shared characteristics of successful online health interventions (e.g., longitudinal design), as well as characteristics that significantly influenced the effect sizes of interventions (design of control group, measurement of outcome variables, and demographic features of participants). The decreasing effect sizes of social-media-based health interventions confirmed the limited effects of health communication in sustaining health behavior changes (Freimuth & Quinn, 2004). This finding highlighted the challenges of computer-mediated health intervention in achieving long-term effectiveness, and provides guidance for design of future interventions.

Conclusion

Technology does not automatically bring benefits to health communication interventions. It depends in part on specific application of these interactive features. Today, Web 2.0 has increasingly been used to disseminate health information and education, bringing both opportunities and challenges (Nordqvist et al., 2009). Despite the endeavors of applying social media, online support groups, interactivity, and other new technology features to health interventions, the overall results have been mixed and the degree of effectiveness remains unclear (Lustria et al., 2007). By conducting three meta-analytical reviews, the current research generated cumulative knowledge of computer-mediated health interventions with the random-effects weighted mean effect sizes found to be statistically significant for social-media-based health intervention, online support groups, and online interactive health interventions.

Moreover, a series of analyses were conducted to identify the variables that moderated the general effects of these three types of online health interventions. In Study 1, social-media-based health interventions categorically measuring outcome variables turned out to have significantly higher effect sizes, and they decreased by .01 given an additional week after the intervention. In Study 2, the effect sizes of online support groups for chronic disease were found to be significantly lower than the effect sizes for mental health issues and for eating disorder. In addition, the online support group conducted with a student sample had significantly higher effect sizes than the support group conducted with participants including mixed social-economic status. Besides utilizing social-economic status as a moderator, an additional year of the participants' mean age and one percentage of female participants in the support group reduced the weighted mean effect sizes by .02 and by .01 respectively. In Study 3, the online health interventions with interactive features, effect sizes for mental health were found to be significantly higher than the effect sizes for substance abuse, physical activity, tobacco use, and chronic diseases. Regarding the intervention design, the studies with no intervention as control group produced higher effect sizes than those with static informative interventions as control group. Moreover, interventions with weekly treatment were found to be more effective than the interventions with the less frequent treatment or one-shot treatment. Given an additional week of interactive health intervention increasing the effect sizes increased by .02. With regards to the participants, studies with at-risk population produced higher effect sizes than healthy adults, and an additional percentage of female participants increased the effect sizes by .005.

Overall, the identification of moderators in these three studies inform health communication scholars and practitioners in designing online health interventions. In general, social media based interventions, online support groups, and interactive interventions are all effective according to the point estimates. These significant moderators guide researchers when proposing future interventions regarding the ideal population, best design, and how to measure specific variables. Additionally, uncovering the nonsignificant moderators provide scholars and practitioners with a greater insight into these general results. Given the potential promise of applying computer-mediated communication to health interventions, a better understanding of the effectiveness and moderating factors of CMHC will benefit health education and public health at the macro-level.

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Notes

1. According to Borenstein, Hedges, Higgins, and Rothstein (2009), fixed-effect model with categorical moderator assumes that all studies in one subgroup share a common effect size, while mixed-effected model allows true variation of effects within the subgroups of studies.

2. Zarit Burden Interview was operationalized as social support by referring to Rodakowski and his colleagues' (2012) study, which applied The Zarit Burden Interview to measure social support.

3. The categorization of health topics was based on Healthy People 2020 (2015) at http://www.healthypeople.gov/2020/topicsobjectives2020/default

4. The categorization of outcome variables is based on Rains and Young's (2009) article.

5. Nutrition, physical activity, and obesity was combined as one category based on the Prevention Status Reports (PSPs) by Centers for Disease Control and Prevention (CDC, 2015) at http://www.cdc.gov/psr/npao/index.html

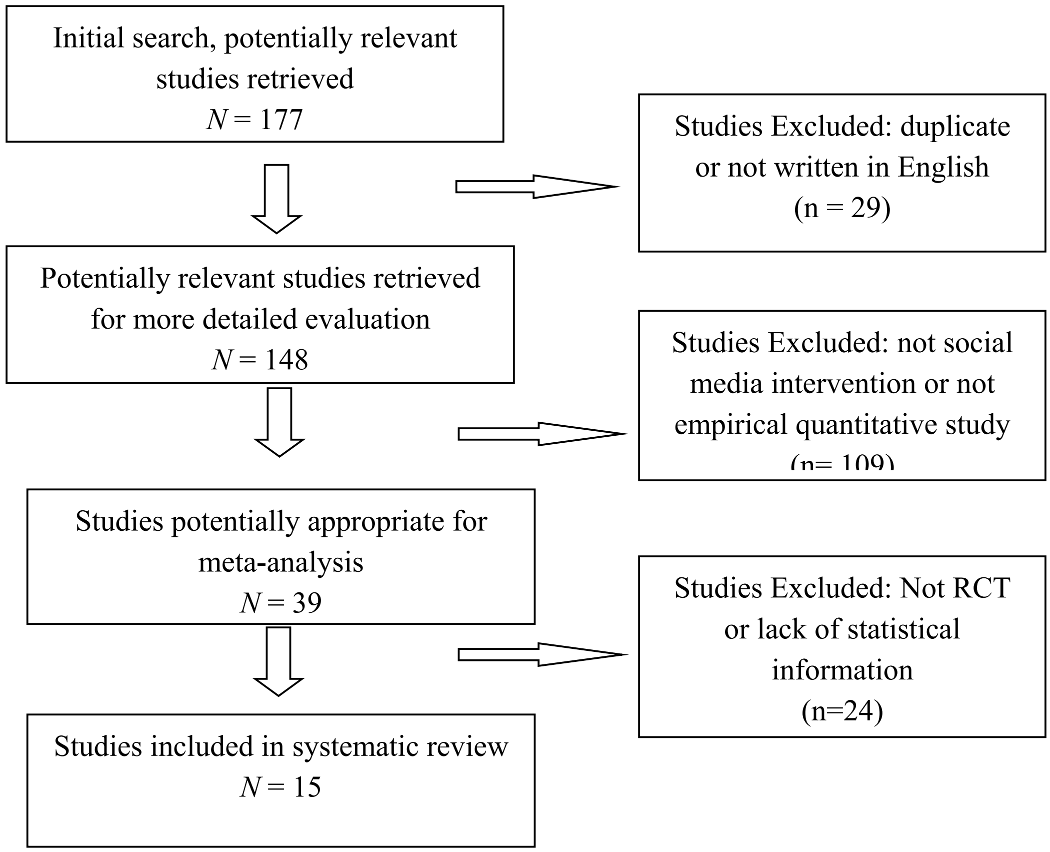

Figure 1. Summary of the selection process used in Study 1 (social-media-based interventions)

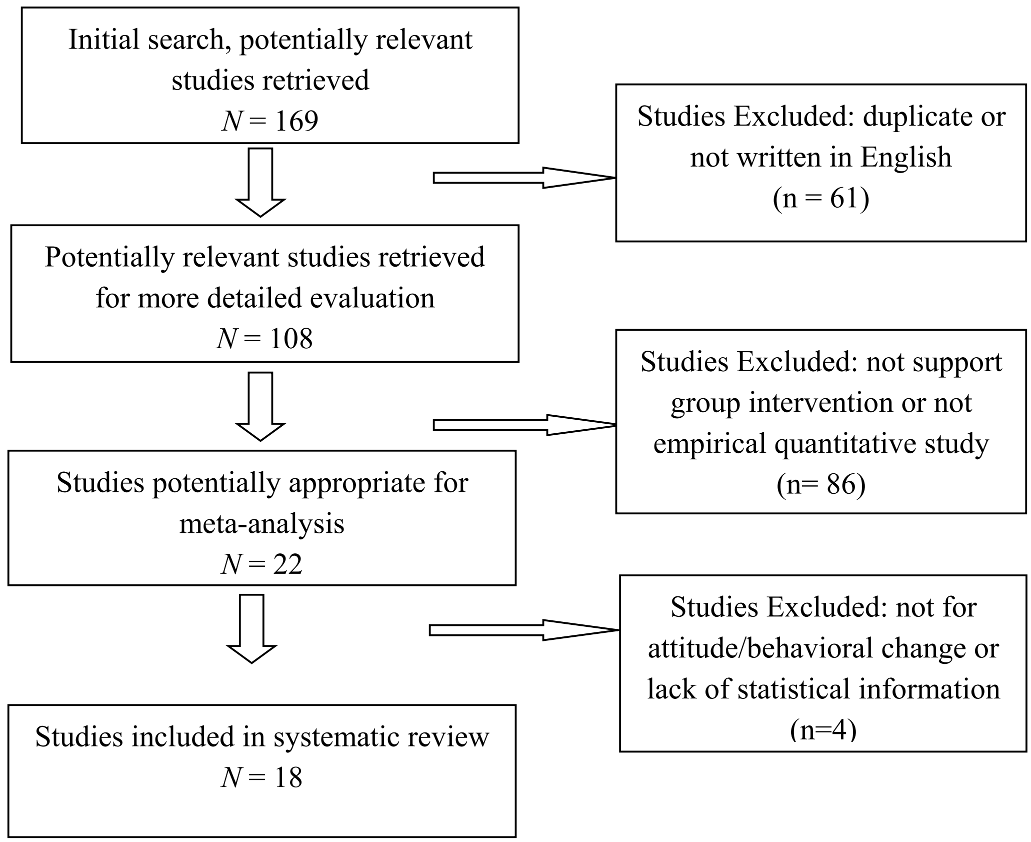

Figure 2. Summary of the selection process used in Study 2 (computer-mediated support groups)

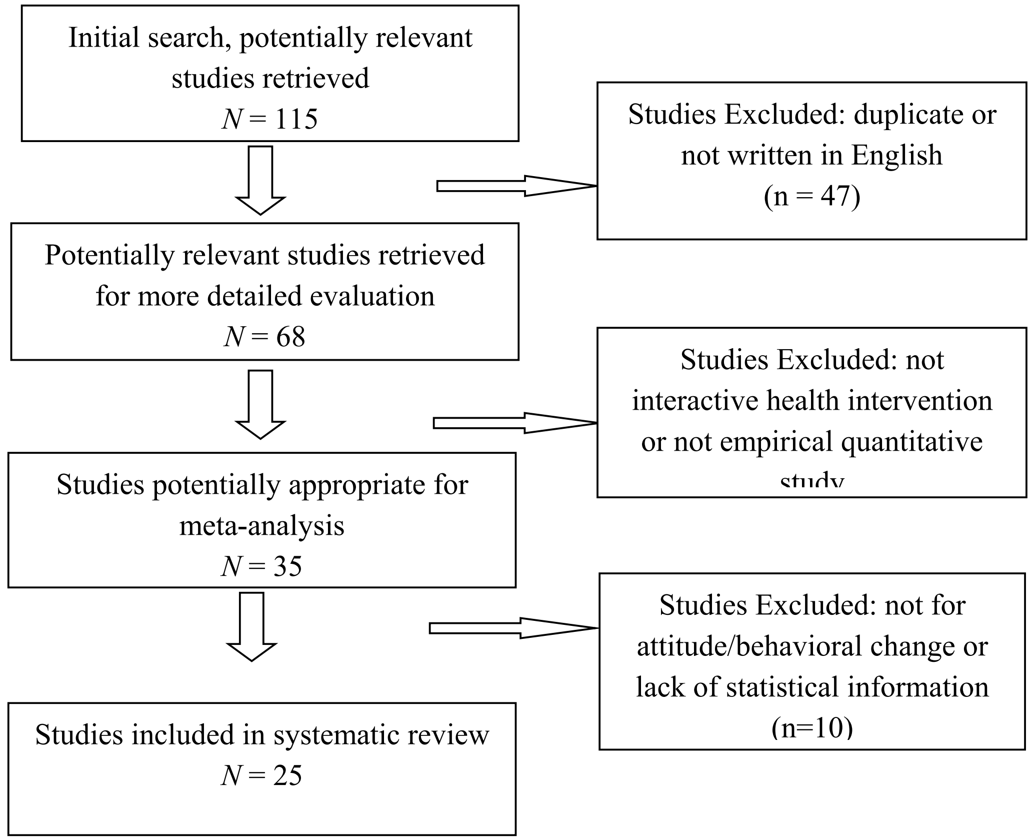

Figure 3. Summary of the selection process used in Study 3 (interactive health interventions)

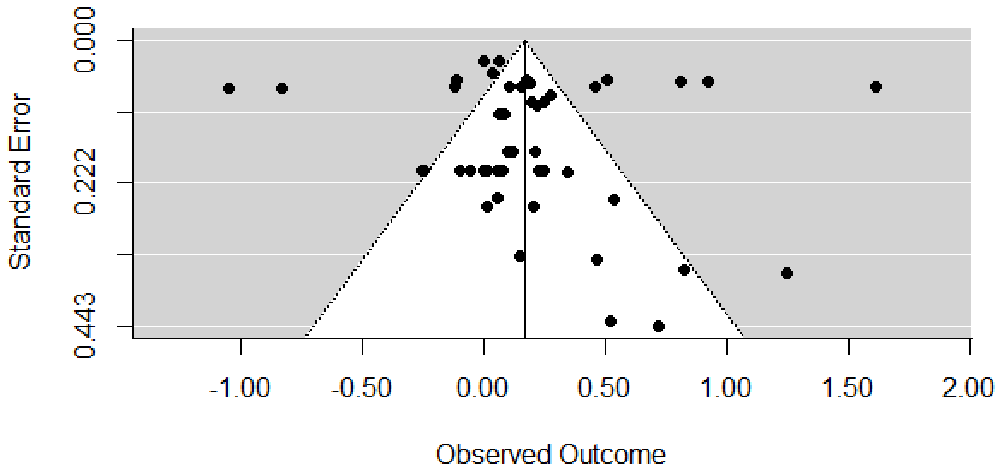

Figure 4. Funnel plot of effect sizes to check publication bias for Study 1

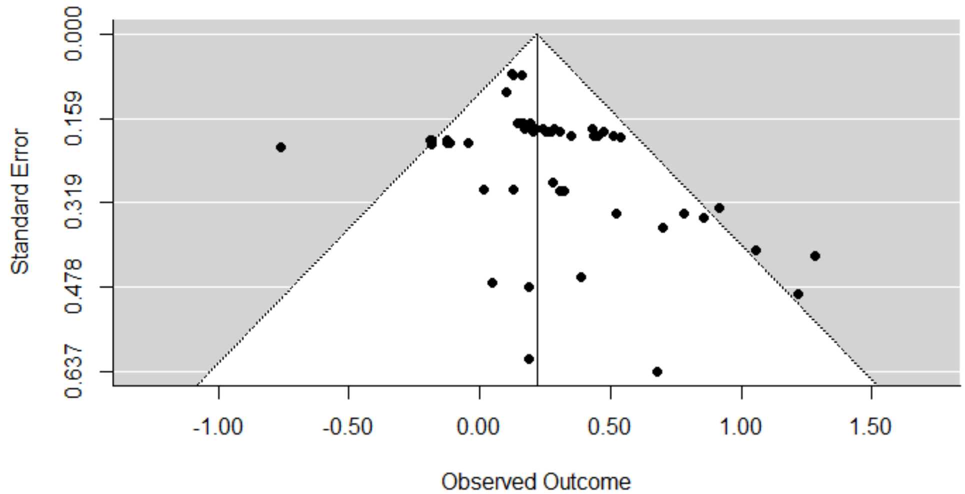

Figure 5. Funnel plot of effect sizes to check publication bias for Study 2

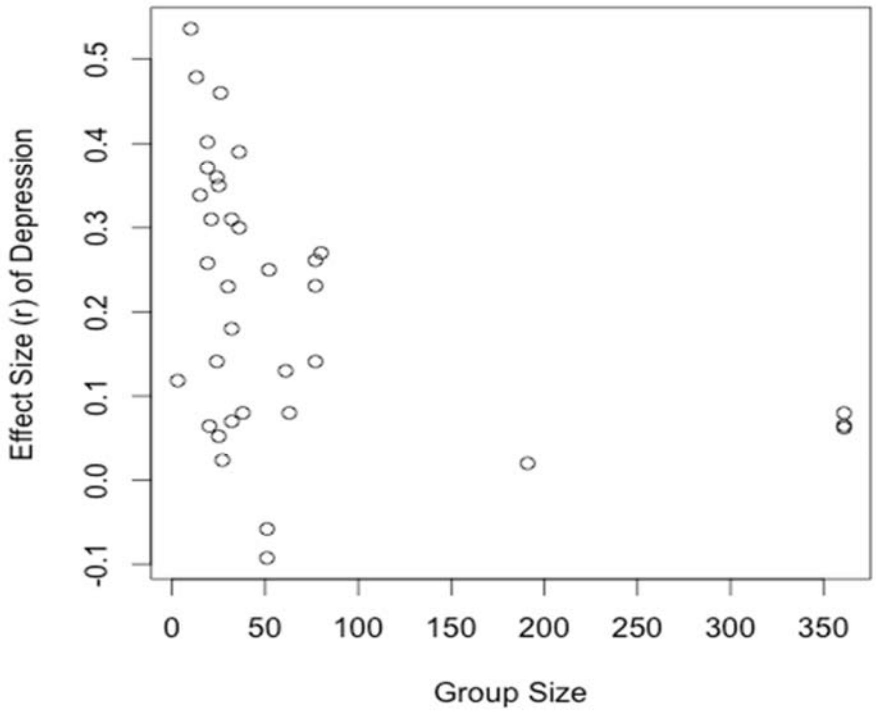

Figure 6. Plot of relationship between group size and effect sizes for depression

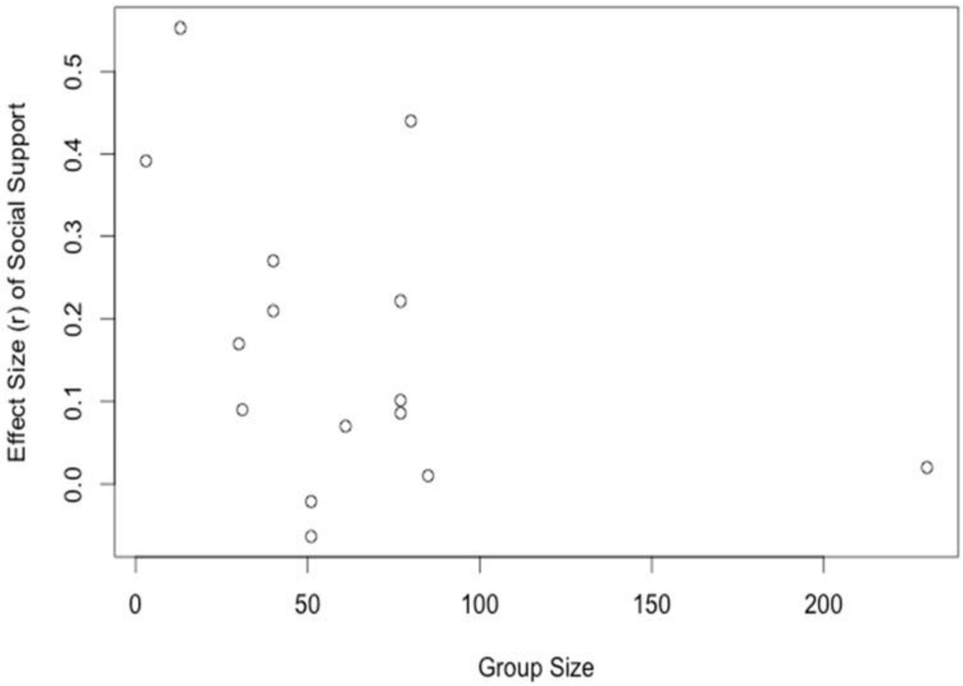

Figure 7. Plot of relationship between group size and effect sizes for social support

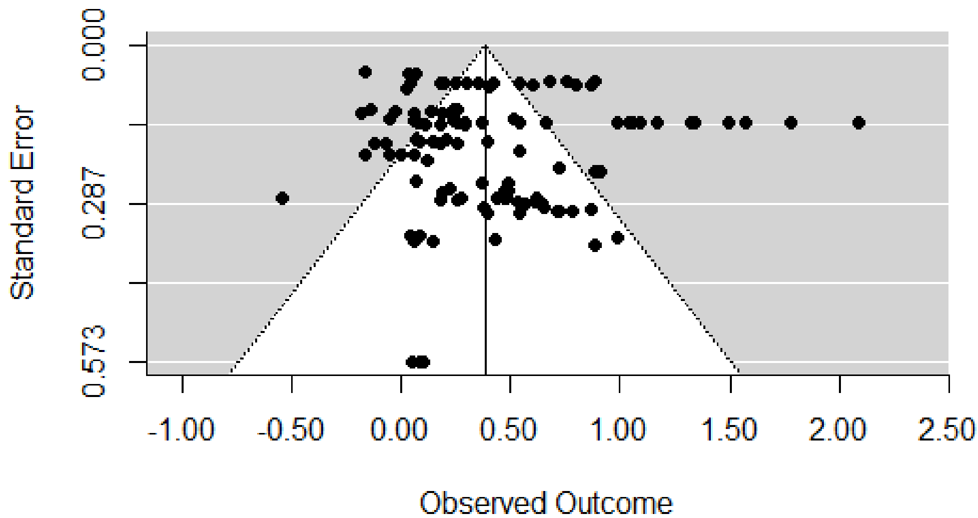

Figure 8. Funnel plot of effect sizes to check publication bias for Study 3

Table 1

Studies Meta-analyzed in Study 1

	Study	Author(s)	Source
1	Features predicting weight loss in overweight or obese participants in a web-based intervention: Randomized trial	Brindal et al. (2012)	Journal of Medical Internet Research
2	Social media-delivered sexual health intervention: A cluster randomized controlled trial	Bull et al. (2012)	American Journal of Preventive Medicine
3	A social media-based physical activity intervention: A randomized controlled trial	Cavallo et al. (2012)	American Journal of Preventive Medicine
4	Effectiveness of a multimodal online well-being intervention: A randomized controlled trial	Cobb & Poirer (2014)	American Journal of Preventive Medicine
5	Motivating physical activity at work: using persuasive social media for competitive step counting	Foster et al. (2010)	Proceedings of the 14th International Academic MindTrek Conference
6	Improving health information access through social networking	Freyne et al. (2010)	Computer-Based Medical Systems (CBMS
7	Metaboli-net: Online groupware system providing counseling guidance for patients with metabolic syndrome	Kuwata et al. (2010)	Studies in Health Technology & Informatics
8	Another time point, a different story: One year effects of a social media intervention on the attitudes of young people towards mental health issues.	Livingston et al. (2014)	Social Psychiatry and Psychiatric Epidemiology
9	Evaluation of a campaign to improve awareness and attitudes of young people towards mental health issues	Livingston et al. (2013)	Social Psychiatry and Psychiatric Epidemiology
10	Using facebook and text messaging to deliver a weight loss program to college students	Napolitano et al. (2013)	Obesity

11	Tweets, apps, and pods: Results of the 6-month mobile pounds off digitally (mobile POD) randomized weight-loss intervention among adults	Turner-McGrievy & Tate (2011)	Journal of Medical Internet Research
12	A randomized trial of a facebook-based physical activity intervention for young adult cancer survivors	Valle et al. (2013)	Journal of Cancer Survivorship

Table 2

Studies Meta-analyzed in Study 2

	Study	Author(s)	Source
1	Psychosexual distress in women with gynecologic cancer: A feasibility study of an online support group	Classen et al. (2013)	Psycho-Oncology
2	Logging on: Evaluating an online support group for parents of children with autism spectrum disorders	Clifford& Minnes (2013)	Journal of Autism and Developmental Disorders
3	An online intervention for reducing depressive symptoms: Secondary benefits for self-esteem, empowerment and quality of life	Crisp et al. (2014)	Psychiatry Research
4	Project onward: An innovative e-health intervention for cancer survivors	Duffecy et al. (2013)	Psycho-Oncology
5	Comparative randomized trial of an online cognitive-behavioral therapy program and an online support group for depression and anxiety	Ellis et al. (2011)	Journal of Cybertherapy and Rehabilitation
6	The effectiveness of an online support group for members of the community with depression: A randomised controlled trial	Griffiths et al. (2012)	Plos One
7	Effect of internet peer-support groups on psychosocial adjustment to cancer: A randomised study	Hoybye et al. (2010)	British Journal of Cancer
8	Social support, opinion leaders, and breast cancer patients' psychosocial health outcomes in online support groups	Kim (2013)	ProQuest Information & Learning
9	Effects of online support group format (moderated vs peer-led) on depressive symptoms and extent of participation in women with breast cancer	Klemm (2012)	Computers, Informatics, Nursing : CIN
10	Virtually supportive: A feasibility pilot study of an online support group for dementia caregivers in a 3D virtual environment	O'Connor et al. (2014)	Journal of Aging Studies
11	Effects of an online support group for prostate cancer survivors: A randomized trial	Osei et al. (2013)	Urologic Nursing
12	Effects of a prototype internet dissonance-based eating disorder prevention program at 1- and 2-year follow-up.	Stice et al. (2014)	Health Psychology

13	A preliminary trial of a prototype internet dissonance-based eating disorder prevention program for young women with body image concerns	Stice et al. (2012)	Journal of Consulting and Clinical Psychology
14	A randomized, controlled study of Internet peer-to-peer interactions among women newly diagnosed with breast cancer	Salzer (2010)	Psycho-Oncology
15	Surviving and Thriving With Cancer Using a Web-Based Health Behavior Change Intervention: Randomized Controlled Trial	Bantum (2014)	Journal of Medical Internet Research

Table 3

Studies Meta-analyzed in Study 3

	Study	Author(s)	Source
1	A randomized trial of an avatar-hosted multiple behavior change intervention for young adult smokers	An et al. (2013)	Journal of the National Cancer Institute
2	Effects of functional interactivity on patients' knowledge, empowerment, and health outcomes: An experimental model-driven evaluation of a web-based intervention	Camerini & Schulz (2012)	Journal of Medical Internet Research
3	MomMoodBooster web-based intervention for postpartum depression: Feasibility trial results	Danaher et al. (2013)	Journal of Medical Internet Research
4	Evaluation of an interactive computer-tailored nutrition intervention in a real-life setting	De Bourdeaudhuij et al. (2007)	Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine
5	Web-based assessment and brief intervention for alcohol use in women of childbearing potential: A report of the primary findings	Delrahim-Howlett et al. (2011)	Alcoholism, Clinical and Experimental Research
6	Factors associated with high use of a workplace web-based stress management program in a randomized controlled intervention study	Hasson et al. (2010)	Health Education Research
7	Internet-based exercise intervention systems: Are more interactive designs better?	Hurling al. (2006)	Psychology & Health
8	Healthy weight regulation and eating disorder prevention in high school students: A universal and targeted web-based intervention	Jones et al. (2014)	Journal of Medical Internet Research
9	Evaluating treatment participation in an internet-based behavioral intervention for pediatric chronic pain	Law et al. (2012)	Journal of Pediatric Psychology
10	Internet-based interactive health intervention for the promotion of sensible drinking: Patterns of use and potential impact on members of the general public	Linke et al. (2007)	Journal of Medical Internet Research

11	Testing of a prototype web based intervention for adolescent mothers on postpartum depression	Logsdon et al. (2010)	Applied Nursing Research : ANR
12	Randomized trial of four noise-induced hearing loss and tinnitus prevention interventions for children	Martin et al. (2014)	International Journal of Audiology
13	Engagement in "my child's asthma", an interactive web-based pediatric asthma management intervention	Meischke et al. (2013)	International Journal of Medical Informatics
14	Optimizing engagement with internet-based health behaviour change interventions: Comparison of self-assessment with and without tailored feedback using a mixed methods approach.	Morrison et al. (2013)	British Journal of Health Psychology
15	An e-health intervention for increasing diabetes knowledge in African Americans	Moussa et al. (2013)	International Journal of Nursing Practice
16	Evaluation of an internet-based physical activity intervention: A preliminary investigation	Napolitano et al. (2003)	Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine
17	Engagement promotes abstinence in a web-based cessation intervention: Cohort study	Richardson et al. (2013)	Journal of Medical Internet Research
18	Examining the added value of audio, graphics, and interactivity in an internet intervention for pediatric encopresis	Ritterband et al.(2013)	Children's Health Care
19	Interactive sections of an internet-based intervention increase empowerment of chronic back pain patients: Randomized controlled trial	Riva et al. (2014)	Journal of Medical Internet Research
20	Skin self-examination education for early detection of melanoma: A randomized controlled trial of internet, workbook, and in-person interventions	Robinson et al. (2014)	Journal of Medical Internet Research
21	Feasibility of an internet-based intervention for improving diabetes outcomes among low-income patients with a high risk for poor diabetes outcomes followed in a community clinic	Ryan et al. (2013)	The Diabetes Educator
22	A web-based sexual violence bystander intervention for male college students: Randomized controlled trial	Salazar et al. (2014)	Journal of Medical Internet Research

23	Web-based cognitive behavioral self-help intervention to reduce cocaine consumption in problematic cocaine users: Randomized controlled trial.	Schaub et al. (2012)	Journal of Medical Internet Research
24	Effects of a web-based intervention for adults with chronic conditions on patient activation: Online randomized controlled trial	Solomon et al. (2012)	Journal of Medical Internet Research
25	Effects of internet-based tailored advice on the use of cholesterol-lowering interventions: A randomized controlled trial.	Webster et al. (2010)	Journal of Medical Internet Research

Table 4

Effect Sizes and Variances for Study 1

Study	Sub-group	N	Age(M)	Channel	Topic	Outcome	ES(d)	V
Brindal_2012	adult; BMI>25	229	47.4	interactive website and a social networking platform	Obesity	website usage	.2057	.0673
						weight loss	.0161	.0672
						web evaluation	.2471	.0094
Bull_2012	16-25 yrs old	1092	19.96	FB group	Sexual health	condom use at last sex	1.6177	.0050
						proportion of protected sex	.9218	.0042
						condom self-efficacy	-.1129	.0038
						condom intentions	.8159	.0041
						drunk or high during sex	.5086	.0039
		804				condom use at last sex	-.1179	.0050
						proportion of protected sex	-.8333	.0054
						condom self-efficacy	-1.0478	.0057
						condom intentions	.4624	.0051
						drunk or high during sex	.1055	.0050
Cavallo_2012	Female undergrads	134	20	Web and FB	physical activity	informational support	.1197	.0299
			21			esteem support	.1007	.0299
			22			companion support	.2165	.0300
			20			physical activity	.1120	.0299
Cobb_2014	adults	1032	46.7	Web-based Social Network; multimodal	well-being	well-being	.1799	.0039
		940	46.7			well-being	.1886	.0043

Foster_2010	nurses; FB users	10		simple mobile device and FB	physical activity	physical activity	.5494	.2075
Freyne_2010	adults	545		SNS SOFA	Info access	attitude	.2759	.0074
Kuwata_2010	adult; BMI>25	10	34.4	Social Network Service	dietary + exercise	dietary awareness	.7542	.2142
Livingston _2014	13-25 yrs	438	19.2	SNS In One Voice	mental health	awareness	.0686	.0050
						efficacy with mental health	.0006	.0050
						personal stigma	.1552	.0050
						social distance	.1579	.0050
						attitude	.1957	.0093
						behavior	.0009	.0050
Livingston _2013	13-25 yrs	403	19.2	SNS In One Voice	mental health	awareness	.0640	.0050
						efficacy with mental health	.0391	.0027
						personal stigma	.0844	.0134
						social distance	.0636	.0134
						behavior	.2217	.0102
Napolitano _2013	Overweight students; BMI 25-50	34	20.47	FB	weight loss	weight loss	.4752	.1210
		35		FB + text message		weight loss	1.2752	.1376
		34		FB		weight loss	.1559	.1180
		33		FB + text message		weight loss	.8464	.1322
Turner-McGrievy _2011	overweight	96	42.9	podcast + mobile (Twitter)	weight loss	weight loss	0	.0417
						physical activity intention	.0829	.0417
						energy intake	.3475	.0423
						fat intake	.0581	.0417
						self-efficacy	0	.0417
						knowledge	-.2487	.0420
					weight loss	eating behavior	.2538	.0420
					weight loss	weight loss	0	.0417
					weight loss	physical activity intention	-.0538	.0417
					weight loss	energy intake	.0833	.0417
					weight loss	fat intake	.0170	.0417

					weight loss	self-efficacy	-.0974	.0417
					weight loss	knowledge	-.2512	.0420
					weight loss	eating behavior	.2291	.0420
Valle_2013	young adult cancer surviv	66	31.7	FB+ PA links +discussion	physical activity	physical activity	.5400	.0629
						quality of life	.0569	.0607

Note: ES= effect size

Table 5

Effect Sizes and Variances for Depression as Outcome Variable in Study 2

Study	Topic	Subgroup	N	Cha-nnel	Age (M)	Study Design	Evl (week)	ES (d)	V
Classen _2013	gyneco logic cancer	sexually distressed, remitted gynecologic cancer patients	27	S + A	43.3	pre-post	4	.0476	.2263
Clifford _2013	Autism	parents of children with autism spectrum disorders	20	S	43	RCT	0	.1290	.0902
Duffey _2013	Cancer	depressed post-treatment cancer survivors	15	A	50	RCT	0	.7200	.1410
			10		46		0	1.2700	.2624
Ellis _2011	depres sion	undergrads with depression	13	A	19.67	RCT	0	1.0906	.1767
Griffiths _2012	depres sion	participants with elevated levels of depressive symptoms	77	A	44.4	RCT	0	.2848	.0322
							24	.4748	.0347
							48	.5412	.0386
Hoybye _2010	cancer	cancer survivors	361	A	53	RCT	4	.1251	.0058
							24	.1602	.0061
							48	.1304	.0063
Klemm _2012	Cancer	woman with Breast Cancer	24	S + A	52.22	RCT	0	.2851	.0808
O'Conn or_2014	Demen tia	dementia caregiver	3	S	60.86	pre-post	1	.2385	.5874
Stice _2014	eating disorde r	young women with body image concerns	19	A	21.6	RCT	48	.8774	.1261
							96	.5336	.1192
Stice _2012	eating disorde r	young women with body image concerns	19	A	21.6	RCT	5	.8000	.1203
Salzer _2010	cancer	women with breast cancer	51	A	50	RCT	16	-.186	.0406
							48	-.1163	.0435
Bantum _2014	cancer	cancer survivors	25	A	52.4	RCT	24	.1048	.0125

Note: Evl= evaluate. ES= effect size. S= synchronous. A= Asynchronous

Table 6

Effect Sizes and Variances (V) for Social Support as Outcome Variable in Study 2

StudyID	Topic	Subgroup	N	Cha-nnel	Age (M)	Study Design	Evl (week)	ES (d)	V
Crisp _2014	depression	adults with psychological distress	77	A	43.94	RCT	0	.1725	.0320
							24	.2038	.0340
							48	.4546	.0377
Ellis _2011	depression	undergrads with depression	13	A	19.67	RCT	0	1.3258	.1876
O'Connor _2014	dementia	Dementia caregiver	3	S	60.86	Pre-post	1	.8507	.6350
Salzer _2010	cancer	women with breast cancer	51	A	50	RCT	16	-.1268	.0405
							48	-.0423	.0434

Note: Evl= evaluate. ES= effect size. S= synchronous. A= Asynchronous

Table 7

Effect Sizes and Variances for Quality of Life as Outcome Variable in Study 2

Study	Topic	Subgroup	N	Cha-nnel	Age (M)	Study Design	Evl (week)	ES (d)	V
Classen _2013	cancer	sexually distressed, remitted gynecologic cancer patients	27	S + A	44.3	pre-post	4	.1918	.2357
Crisp _2014	depression	adults with psychological distress	77	A	43.94	RCT	0	.4354	.0326
							24	.2562	.0341
							48	.3525	.0373
Kim _2012	cancer	breast cancer patients	70	A	50.68	RCT	2	-.1682	.0287
							6	-.1454	.0286
							12	-.1945	.0287
							24	.1509	.0287
Osei _2013	cancer	prostate cancer survivor	20	A	67.2	RCT	6 to 8	.9332	.1125
Salzer _2010	cancer	women with breast cancer	51	A	50	RCT	16	-.1858	.0436
							48	-.1242	.0435

Note: Evl= evaluate. ES= effect size. S= synchronous. A= Asynchronous

Table 8

Effect Sizes and Variances for Self-Efficacy as Outcome Variable in Study 2

Study	**Topic**	**Subgroup**	**N**	**Cha-nnel**	**Age (M)**	**Study Design**	**Evl (week)**	**ES (d)**	**V**
Crisp _2014	depression	adults with psychological distress	77	A	43.94	RCT	0	.2418	.0321
							24	.3063	.0342
							48	.3535	.0373
Salzer _2010	cancer	women with breast cancer	51	A	50	pre-post	16	-.1885	.0406
Salzer _2010	cancer	women with breast cancer	51	A	50	RCT	48	-.7650	.0466

Note: Evl= evaluate. ES= effect size. S= synchronous. A= Asynchronous

Table 9

Effect Sizes and Variances for Study 3

Study	Subgroup	N	Age (M)	Study Design	Topic	Outcome	ES(d)	V
An _2013	18-30 yrs old; smoker	887	24.07	RCT	Smoking	Abstinence from cigarette	.1759	.0045
						Change in number of days of alcohol use	.0380	.0045
						Eating breakfast	.4219	.0046
						Exercise	.2990	.0046
		876				Abstinence from cigarette	.2511	.0046
						Change in # of days of alcohol use	.1937	.0046
						Eating breakfast	.5366	.0047
						Exercise	.3513	.0046
Camerini _2012	Patients with fibromyalgia syndrome (FMS)	100	49.93	RCT	Health literacy	Health outcomes (low score is better)	.0571	.0400
						Knowledge	0	.0400
		101				Health outcomes (low score is better)	.0624	.0396
						Knowledge	.1665	.0397
Danaher _2013	Women with mild to moderately severe depression	53	31.9	Pre/post	Depress-ion	Health condition (low score is better)	1.7882	.0200
						Depression status (low score is better)	1.5840	.0200
						Negative thoughts (low score is better)	1.1013	.0200
						Changes in activation	1.3528	.0200
						Knowledge, competence in being a mom	.6667	.0200
						Self-efficacy	1.0667	.0200
						Relationship with parents	.0719	.0200
						Health condition (low score is better)	2.1000	.0200
						Depression status (low score is better)	1.5036	.0200
						Negative thoughts (low score is better)	.9961	.0200
						Changes in activation	1.3366	.0200

						Knowledge, competence in being a mom	1.0476	.0200
						Self-efficacy	1.1765	.0200
						Relationship with parents	.2564	.0200
De Bourdeaudhuij _2007	Adults	232	39.1	Quasi	Nutrition	Fat intake	.5135	.0179
		213					.5405	.0195
Delrahim-Howlett _2011	Risky drinking women	131	26.33	RCT	Drinking	Reduction in RDO	.0835	.0306
						MDPO	.1466	.0307
		64	26.33			Sustained reduction in RDO	.0650	.0626
Hasson _2010	Adults	303	40	RCT	Stress management	Use of program	.2533	.0136
		303	40			Expectation of program	.2397	.0136
Hurling _2006	Adults without using medication	66	35	RCT	Exercise	Engagement	.4950	.0639
						Perception of exercise	.3744	.0631
						Expectation of exercise	.4764	.0705
						Satisfaction with motivation	.4968	.0706
						Intention	.2268	.069
		43				Satisfaction with motivation	.3983	.0953
		35				Satisfaction with motivation	.9030	.1385
		43				Behavior	.5481	.0970
		35				Behavior	.4425	.1296
Jones _2014	9th grade overweight students	111	14.3	Quasi	Obesity	Height and weight	.5391	.0373
		91				Fruit consumption	.9132	.0531
						Veg consumption	.1169	.0441
						Soda consumption	.7223	.0497
						Physical activity	.885	.0526
	Subgroup (concerned about weight)	36				Psychosocial (weight concerns)	1.0000	.1250
Law _2012	Adolescents with chronic pain	48	14.31	RCT	Pediatric Chronic Pain	Pain intensity	.6656	.0885
						Activity limitation	.8810	.0920
Linke _2007	Adults	421	38.9	Quasi	Drinking	Alcohol dependency	.7957	.0051
						Alcohol problem	.8640	.0052
						Mental health	.6005	.0050
		520				Alcohol dependency	.7581	.0041

						Alcohol problem	.8856	.0042
						Mental health	.6810	.0041
Logsdon _2013	Adolescent parents	138	16.76	Quasi	Attitude towards depression	Mental health acceptability	.2086	.0296
						Stigma	.0695	.02943
						Attitude towards seeking help	.3944	.0300
Martin _2013	Fourth grade students	506	9.5	RCT	Hearing loss and tinnitus	Attitudes	.0584	.0150
							-.0282	.0146
		446					.0552	.0188
		506				Intended behaviors	-.1853	.0149
							-.1410	.0137
		446					.2387	.0176
		506				Knowledge	.1914	.0148
							.1402	.0143
		446					.2376	.0183
Morrison _2013	Students who experience non-clinical or mild bowel complaints	125	30.17	RCT	Behavioral change related to bowel syndrome	Self-efficacy	.2580	.0324
						Engagement of the design	-.0718	.0322
Moussa _2013	African Americans with diabetes and low diabetes literacy	46	52	RCT	Diabetes	Diabetes knowledge	.3863	.0886
							.7225	.0926
							.7372	.0929
							.7962	.0938
Napolitano_2003	Healthy adults	57	42.8	RCT	Physical activity	Moderate physical activity	.1930	.0723
						Walking	.2590	.0806
		52				Moderate physical activity	.5360	.0828
						Walking	.6210	.0829
Richardson_2013	Adults	1033	N/A	One-shot	Quitting smoking	Quit attempt	-.1665	.0024
							.0296	.0026
							.0709	.0028
Ritterband_2006	Children 5-12 yrs old	49	7.98	RCT	Pediatric encopresis	Knowledge	.5743	.0850
						Motivation	.6514	.0860
						Readiness to change	.1800	.0820
Riva _2014	> 18 years	51	47.29	RCT	Empower-ment	Empowerment	.6300	
						Empowerment	.4400	
					Medication misuse	Medication misuse	.2800	
							-.5500	
						Pain burden	.4800	
							.4900	
Robinson _2014	Melanoma patients and SSE partners	235	55.19	RCT	Early detection of melanoma	Behavior	.2944	.0205
						Comprehension	.1818	.0204
						Self-efficacy	.1102	.0204

Salazar _2014	Male college students	215	20.38	RCT	Sexual violence	Prosocial intervening behaviors	.3700	
						Sexual violence perpetration	.2900	
Schaub _2012	Cocaine-using	33	34.2	RCT	Cocaine	Cocaine consumption	.0380	.1241
		30					.0588	.1340
		11					.0937	.3933
		33				Cocaine dependence	.0902	.1242
		30					.0620	.1340
		11					.1091	.3934
		30				Depression	.1508	.1343
		11					.0570	.3930
Solomon _2012	18-64 yrs old; adults	126	N/A	RCT	Adults with chronic conditions	Patient activation	-.1245	.0320
							.1827	.0321
Webster _2010	Adults	2099	56	RCT	Cholesterol lowering	Increased treatment	-.0497	.0174
						Engagement	.3992	.0057
						Using cholesterol-lowing margarine	.0239	.0063

Note: Evl= evaluate. ES= effect size.