Networked Social Influence: Online Social Network Physical Activity Interventions for Young Adults

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Networked Social Influence: Online Social Network Physical Activity Interventions for Young Adults

Abstract
Sedentary lifestyle significantly increases the risks of chronic disease and all-cause mortality. Nevertheless, low levels of physical activity among young adults remain a serious nationwide problem, with 69% of Americans 18 to 24 years of age failing to meet the federal guidelines for both aerobic and muscle-strengthening activity in 2014. Among all the social and environmental factors affecting physical activity levels, interpersonal social networks are one of the most prominent targets for cost-effective interventions. In particular, online social networks are a highly attractive resource for large scale health initiatives given their capacity to disseminate interventions easily while simultaneously facilitating social influence dynamics. This dissertation examines online social networks’ efficacy and mechanisms in increasing physical activity among young adults. The dissertation comprises three experiment studies. The first study employed a 3-arm randomized controlled trial (RCT) to examine the effects of basic website, promotional media messaging, and web-based anonymous online networks in increasing exercise class enrollment. The results showed among 217 university graduate students anonymous online networks were more effective than the basic website in increasing exercise class enrollment. The second study built upon the first study and employed a 2 by 2 factorial RCT to compare the effects of supportive versus competitive interactions and individual versus team incentives through web-based online networks in increasing exercise class attendance. The results showed among 790 university graduate students, social comparison was more effective in increasing exercise class attendance than social support. There was no significant difference between individual and team incentives in increasing class attendance. The third study shifted the technological platform and employed a mobile application. It tested the efficacy of an online network mobile app intervention in increasing daily active minutes objectively recorded by a fitness tracking device (Fitbit zip) in comparison with a control condition where individuals used the app by themselves without any connection with other people. Results showed among 91 young African American women, the online networks did not impact the primary outcome, daily active minutes. Self-reported physical activity significantly increased after the intervention program irrespective of intervention arms. Online networks were effective in increasing daily engagement with the fitness tracking device and the mobile app in comparison with the control condition. In addition, descriptive analyses on theoretical variables indicated that young African American women perceived low levels of peer norm and social support on physical activity in general. Online networks entail great potentials in promoting physical activity for young adults. More research is needed to fully understand the long-term effects and mechanisms of online networks in promoting physical activity and in other health behavior domains.

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NETWORKED SOCIAL INFLUENCE:
ONLINE SOCIAL NETWORK PHYSICAL ACTIVITY INTERVENTIONS FOR
YOUNG ADULTS

Jingwen Zhang

A DISSERTATION

in

Communication

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2016

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NETWORKED SOCIAL INFLUENCE:
ONLINE SOCIAL NETWORK PHYSICAL ACTIVITY INTERVENTIONS FOR
YOUNG ADULTS

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ABSTRACT

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ONLINE SOCIAL NETWORK PHYSICAL ACTIVITY INTERVENTIONS FOR
YOUNG ADULTS

Jingwen Zhang
John B. Jemmott III

Sedentary lifestyle significantly increases the risks of chronic disease and all-cause mortality. Nevertheless, low levels of physical activity among young adults remain a serious nationwide problem, with 69% of Americans 18 to 24 years of age failing to meet the federal guidelines for both aerobic and muscle-strengthening activity in 2014. Among all the social and environmental factors affecting physical activity levels, interpersonal social networks are one of the most prominent targets for cost-effective interventions. In particular, online social networks are a highly attractive resource for large scale health initiatives given their capacity to disseminate interventions easily while simultaneously facilitating social influence dynamics. This dissertation examines online social networks’ efficacy and mechanisms in increasing physical activity among young adults. The dissertation comprises three experiment studies. The first study employed a 3-arm randomized controlled trial (RCT) to examine the effects of basic website, promotional media messaging, and web-based anonymous online networks in increasing exercise class enrollment. The results showed among 217 university graduate students anonymous online networks were more effective than the basic website in increasing exercise class enrollment. The second study built upon the first study and employed a 2
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CHAPTER 1
INTRODUCTION

Sedentary lifestyle is an escalating epidemic (Dunstan, Howard, Healy, & Owen, 2012; Hamilton, Healy, Dunstan, Zderic, & Owen, 2008; Thorp, Owen, Neuhaus, & Dunstan, 2011). Despite the known benefits of physical activity for a range of chronic diseases (Krishnan, Rosenberg, & Palmer, 2009; Oguma, Sesso, Paffenbarger, & Lee, 2002; Samitz, Egger, & Zwahlen, 2011; Sattelmair et al., 2011; Wen et al., 2011), 69% of Americans 18 to 24 years of age failed to meet the federal guidelines for both aerobic and muscle-strengthening activity in 2014 (National Center for Health Statistics, 2015). Due to major life event changes associated with the independence and work schedule, a high proportion of young adults are sedentary or irregularly active (Gordon-Larsen, Nelson, & Popkin, 2004; Woods, Mutrie, & Scott, 2002). This statistic is alarming because sedentary habits developed in younger ages are likely to continue into later life (Kvaavik, Tell, & Klepp, 2003).

This dissertation addresses an urgent public health problem: the lack of efficacious intervention strategies to encourage young adults to engage in physical activity (Calfas et al., 2000; Kahn et al., 2002). Among all the social and environmental factors affecting physical activity levels (Addy et al., 2004; Martin & Savla, 2011), interpersonal social networks are one of the most prominent targets for cost-effective interventions. From an egocentric or local perspective, a social network is defined as the web and characteristics of social relationships that surround an individual. The strength of social network theories rests on the assumption that the characteristics of the network itself are largely responsible for determining individual behavior. A host of theories and
evidence supports the view that social networks, giving rise to various social functions such as social influence, social comparison, companionship, and social support, influence people’s behaviors (Berkman, Glass, Brissette, & Seeman, 2000; Heaney & Israel, 2008; Smith & Christakis, 2008; Valente, 2012). In an effort to clarify many loosely and interchangeably used terms and causal pathways, Berkman et al. (2000) proposed a conceptual model of how social networks impact health. Social networks impact health behaviors through four primary pathways: (1) provision of social support; (2) social influence; (3) social engagement and attachment; and (4) access to resources and material goods. Although Berkman’s overarching model integrates multiple causal pathways, it stays at the conceptual level and falls short of making specific predictions and guiding the development of policy or intervention to improve the health of the public. On a smaller scope, linking the literature of social network and the literature of social psychology, Contractor and DeChurch (2014) proposed the Structured Influence Process (SIP) framework. SIP explains how social networks and human social motives (i.e., the process of social influence) can be structured to enact social influence within a community. Specifically, it discusses how to leverage existing social ties and create new social ties to prompt social interactions for attitude and norm change within the community.

The few empirical studies that have tested interventions implemented with social networks (Valente, 2012; Wang, Brown, Shen, & Tucker, 2011) have focused on participants’ existing social networks and have required a great amount of resources in creating and measuring the network characteristics. Because local networks constantly evolve, experimenting with different network characteristics often becomes impractical. Past social network interventions focused on identifying and training opinion leaders to
influence other network members. There is a lack of rigorous experiments that test the multiple causal pathways from social network characteristics to psychological mechanisms to health behaviors and outcomes.

While previous social network interventions focused on participants’ existing social networks, the advent of online social networks provides new opportunities to rethink this line of research and to design new approaches that could potentially test some theoretical pathways (e.g., providing social support or changing perceived social norms) through which social networks impact health behaviors. Online social networks transcend geographic boundaries and allow individuals to construct new social relationships through various communication modalities. Especially online social network interventions can allow people to connect and interact with other people who are engaging in the targeted behavior through constructing new networks (Centola, 2010, 2011, 2013).

Currently, the most commonly used online social network intervention approach is to use existing general social networking sites (SNSs) as a communication channel to deliver intervention contents (De la Torre-Diez, Diaz-Pernas, & Anton-Rodriguez, 2012; Ding & Zhang, 2010; Shaw & Johnson, 2011). For instance, in an online physical activity intervention, Cavallo et al. (2012) created a study-specific Facebook group as the intervention platform. Participants randomized to the intervention Facebook group could share information and discuss issues related to exercise with other participants on the group page. Although the study found an overall increase in both perceived social support and self-reported physical activity throughout the program, the two intervention results were not statistically significant in comparison with the control. Similar interventions
were often not guided by relevant theoretical frameworks and combined the social network component with other commonly used online behavior change techniques such as goal-setting and personalized feedback (Vandelaanotte et al., 2016). Two meta-analyses did not identify effects of online social network interventions on health behavior change (Laranjo et al., 2015; Maher et al., 2014). Maher and colleagues (2014) found effect sizes for behavior change ranged widely and were non-significant in general based on 10 studies (Cohen’s $d = -0.05$, 95% CI [0.45-0.35] to 0.84, 95% CI [0.49-1.19]). Although Laranjo and colleagues (2014) found a small positive effect based on 12 studies (Hedges’ $g = 0.24$, 95% CI [0.04-0.43]), it is important to note that after dropping the two studies by Centola (2010, 2011), the effect dropped to 0.05 and became non-significant. This indicates there is no systematic guidance on how to design and implement online social network health interventions.

This dissertation aims to advance our theoretical discussion on online social network interventions and provide empirical evidence that demonstrates the efficacy and causal pathways of online social network interventions, focusing on promoting young adults’ physical activity. Using both websites and mobile applications as the intervention infrastructure, this dissertation analyzes behavioral data on physical activity and self-reported psychological measures collected from three randomized controlled trials (RCTs). Results of the dissertation shed new light on the role played by online social networks and social influence mechanisms in promoting everyday physical activity.
Overview of the Dissertation

This dissertation is organized as follows. To understand the core affordances and theoretical importance of online social networks in health promotion, Chapter 2 first conceptualizes social networks and their relations to health. The chapter then reviews empirical evidence regarding online social network health interventions. Chapter 3 briefly reviews three theoretical frameworks relevant to social network influence and further synthesizes previous literature and discusses how to design online social networks for promoting health behavior change. Guided by the theoretical discussions, Chapter 4 summarizes the dissertation’s innovation and main research questions.

Chapter 5 presents two web-based online network interventions among university graduate students (Study 1 & 2). Study 1 is a 3-arm RCT that tested the efficacy of anonymous online networks in comparison with promotional media messaging and a basic control website. Results showed social influence from anonymous online peers was more effective than promotional media messages in increasing exercise class enrollment. Built on Study 1, Study 2 presents a web-based online network intervention that compared two social influence mechanisms, social support and social comparison, among university graduate students. This 2 by 2 factorial RCT compared the effects of supportive versus competitive interactions and individual versus team incentives through web-based online networks in increasing exercise class attendance. Results showed social comparison elicited through online networks provides a greater source of social incentive for increasing exercise class attendance than did social support. Social comparison effects were equally strong regardless of whether it was based on individual or team incentives.
Moving beyond using website as the intervention platform, Chapter 6 presents a mobile app based online network intervention among young African American women from the community. This 2-arm RCT tested the efficacy of online networks in increasing daily active minutes in comparison with a control condition where individual participants used the mobile app by themselves. The primary outcome was individuals’ daily active exercise minutes objectively recorded by a fitness tracking device (Fitbit zip). Results showed the online network intervention did not have a significant impact on the primary outcome. All participants significantly increased their self-reported physical activity throughout the program. Online networks were more effective in increasing daily engagement with the fitness tracking device and the mobile app compared with the control condition. In addition, descriptive analyses suggested that young African American women generally perceived low levels of peer norm and social support for physical activity.

The final chapter, Chapter 7, summarizes the major findings of this dissertation in relation to existing research literature, discusses their theoretical and practical implications, points to limitations of the dissertation, and suggests directions for future research.
CHAPTER 2
LITERATURE REVIEW

A host of theories and evidence supports the view that social networks, giving rise to various social functions such as social influence, social comparison, companionship, and social support, influence people’s behaviors; but studies have not consistently demonstrated that intervening using online social networks is efficacious in improving physical activity. One primary reason for a lack of results is that most studies were driven by technology and not designed based on behavior-change theories. The few studies that employed behavior change theories, drew upon theories that were centered on individual behavioral determinants and seldom incorporated insights of social influence that comes from individuals’ social networks. In this chapter, I provide clear conceptualizations of social networks and their relations to health and summarize empirical evidence on online social network health interventions.

Social Networks and Health

Despite the social network theory and method developed in fields such as psychology, sociology, and physics since 1930s, only relatively recently have scholars utilized a more explicit network approach in the health domain. A social network approach focuses on the structural determinants of health and various mechanisms underlying the impact of social networks on health outcomes, assuming social actors and social actions are interdependent and social relations facilitate the flow of information and influence (Smith & Christakis, 2008; Wasserman & Faust, 1994; Wellman & Berkowitz, 1988).
Social networks are networks in which the nodes are people, or sometimes groups of people, and the ties represent some form of social interaction between them (Newman, 2010). While the nodes of a social network, individual persons, are straightforward and easily identifiable, the ties can be ambiguous because there exist a multitude of social interactions, ranging from kinship, friendship, colleagueship to virtual online relationships, with very different levels of the quantity and quality of social interactions. Each individual is embedded in a complex web of social interactions that could impact on health.

The defining character of social network research is that social networks have emergent properties not explained by the individual constituent parts (i.e., attributes of the nodes and ties) and also not present in the parts. It is not appropriate to generalize from individual preferences and behaviors to the aggregate outcomes or to infer individual preference and behavior from aggregated patterns (Granovetter, 1978; Schelling, 1978). As Hall and Wellman (1985) summarized, network analysis “focuses on the characteristic patterns of ties between actors in a social system rather than on characteristics of the individual actors themselves. Analysts search for the structure of ties underlying what often appears to be incoherent surface appearances and use their descriptions to study how these social structures constrain network member’s behavior” (p.26).

The effects of social networks on health and mortality were originally theorized and demonstrated empirically in the 1970s (Berkman & Syme, 1979; Cassel, 1995; Cobb, 1976). Social support was theorized as the mechanism linking social networks to better health. Social network members can provide informational, emotional, appraisal, and
instructional support that could moderate and buffer the deleterious effects of stressors in major life transitions (House, Landis, & Umberson, 1988). Although social support remains the most prominent research focus to date, more mechanisms have been proposed and examined since then. For instance, Berkman et al. (2000) proposed a conceptual model of how social networks impact health. Social network-level factors (independent variables) influence psychosocial mechanisms (mediating variables) that impact on individual-level health determinants and health outcomes (dependent variables). Specially, social network-level factors include structural (e.g., size, density, homogeneity, centrality) and tie characteristics (e.g., reciprocity, intimacy, duration). Psychosocial mechanisms include social support (e.g., emotional, informational, appraisal, instrumental support), social influence (e.g., norms, imitation, social comparison), social engagement and attachment (e.g., church attendance, community belonging), person – to – person contacts (e.g., pathogen exposure), and access to resources (e.g., money, foods, jobs, information). Individual-level health determinants refer to specific health behaviors (e.g., smoking, drug use, physical activity) and physiological pathways (e.g., immune system function).

Identifying the relationships between social network characteristics and health risks helps researchers to further design disease prevention and control strategies (Valente, 2012). For instance, based on egocentric (or local) networks (Campbell & Lee, 1991), previous research suggests the size of the health advice and the financial support networks is positively related to condom use norms (Latkin, Forman, Knowlton, & Sherman, 2003) and older people embedded in less resourceful network types are at greater risk for alcohol abuse and physical inactivity (Shiovitz-Ezra & Litwin, 2012).
Based on sociometric (or complete, global, saturation) networks, previous research suggests biases in favor of connections between network members with similar characteristics in sexual networks contribute to disparities in prevalence of STDs and HIV (Laumann & Youm, 1999; Schneider et al., 2013).

Although these observational studies provide preliminary evidence linking social network characteristics to health behaviors and outcomes, there are major methodological problems. First, due to the complex and often subjectively defined social relationships, survey measures for assessing network characteristics lack good validity and reliability. For instance, people are more likely to recall strong ties as opposed to weak ones (Bondonio, 1998) and differ in their ability to perceive accurately the informal patterns of interpersonal relationships in their social networks (Casciaro, 1998). Biases elicited from different survey questions may render measurements of network characteristics incomparable across studies. Second, more importantly, the causal mechanisms suggested in the Berkman model cannot be easily established in observational research. It is possible that homophily, the propensity of likes to associate with likes in forming social networks and other confounding variables could lead to both clustered social network ties and co-occurrence of certain behaviors, diseases, and illnesses (McPherson, Smith-Lovin, & Cook, 2001; Shalizi & Thomas, 2011). More experimental research thus is needed to examine the causal effects and mechanisms of social networks on health.

The above discussed research findings on the relations between social network characteristics and health outcomes suggest that intervening on people’s social networks can potentially accelerate behavior change and improve health at the collective level. However, currently there is no systematic guidance on how to design and implement
social network health interventions. Some researchers focused on social support interventions (Hogan, Linden, & Najarian, 2002) whereas others focused on social influence interventions (Wang, Brown, Shen, & Tucker, 2011). Social support interventions usually involve direct or indirect provision of actual or perceived social support in the target population. For instance, Wing and Jeffery (1999) compared the effects of a weight-loss intervention in either friendship support networks or stranger support networks and found friendship support networks were more effective in impacting on weight loss. Hogan et al. (2002) summarized all types and effects of social support interventions and concluded that there was some support for the overall usefulness of social support interventions. However, because of the large variety of different treatment protocols and areas of application, there is still not enough evidence to conclude which interventions work best for what problems. Strictly speaking, in Hogan’s summary, some social support interventions that were delivered to individuals instead of networks of individuals should not be considered as social network interventions.

Social influence interventions, on the other hand, target networks of individuals and oftentimes employ opinion leaders in the network as the intervention deliverers. For instance, Amirkhanian et al. (2005) trained network leaders to communicate HIV prevention advice to their network members and found experimental network members reported a significant decline in unprotected sexual intercourse. Wang et al. (2011) systematically reviewed social network interventions focusing on condom promotion and restricted social networks as groups of individuals who self-identified as groups prior to the research. Similar to Hogan et al. (2002), they found large differences in how social network members were identified and involved in the interventions. Among nine studies
with control groups, eight showed significant improvements in at least one measure of condom use. This qualitative systematic review highlights the potential utility of social network-based condom promotion programs and asks for more research to explore effective network intervention strategies.

Although social network interventions appear promising in tackling public health problems, they are more difficult to implement and evaluate compared with individual-based interventions. Especially, altering people’s network connections is probably more difficult than intervening on existing network members. For instance, letting people establish new social connections or eliminate old connections may not be feasible in a relatively short period. In this regard, online social networks provide a promising platform to further explore methods of constructing and alternating networks for health promotion.

**Online Social Network Health Interventions**

Online social networks are networks created and maintained on online platforms. They are commonly referred to as social networking sites (SNSs). SNSs are defined as web-based services that allow individuals to construct their own profiles and build a network of connections with other users within the system (Boyd & Ellison, 2007). Since Boyd and Ellison defined SNSs in 2007, the range of technological platforms, functions, and characters of SNSs continues to expand. To date, different SNSs focus on different specialties, encouraging anonymized or identified, one-way or two-way, and synchronized or desynchronized communication.
There are generally two types of online social network health interventions. One is the use of existing general SNSs as a communication channel to deliver health interventions. General SNSs such as Facebook and Twitter are not intentionally designed for health campaigns or health-related interactions, yet, organizations and researchers can make use of such platforms for particular health interventions by creating topic-specific pages and groups (De la Torre-Diez et al., 2012; Ding & Zhang, 2010; Shaw & Johnson, 2011). For instance, in an online physical activity intervention, Cavallo et al. (2012) created a study-specific Facebook group as the intervention platform. Participants randomized to the Facebook group intervention joined a Facebook group page using their existing Facebook account, where they could exchange social support. In addition, moderators of the Facebook group posted discussion facilitating questions and related news stories. Participants in the control group received access to an education-only website and received e-mails throughout the study with links to news stories that were provided to the intervention group. Although the study found an overall increase in perceived social support and self-reported physical activity throughout the program, results from the intervention group and the control group were not distinguishable. It is important to note that participants in the intervention group only posted to the discussion board and did not fully utilize the Facebook networking functions such as adding new friends and sharing each other’s progress and setbacks related to exercise.

The other type of online social network health intervention uses health-specific SNSs. Health-specific SNSs include some that are open to people with any health concerns (e.g., PatientsLikeMe, an online patient network), some that are oriented toward people with a specific chronic condition (e.g., TuDiabetes, an online community of
people with diabetes), and some that target people wanting to adopt a healthy lifestyle (e.g., MyFitnessPal, an online portal that provides free calorie counter and diet plan) or to change a particular health-risk behavior (e.g., QuitNet, an online community for smokers and ex-smokers). Researcher designed health-specific SNSs can take on different design elements to answer research questions. For instance, Brindal et al. (2012) designed a social networking site for weight loss. On the website, each participant created a profile page, including a chosen image, personal details, a message board, and a personal or public blog. Connections between participants were requested, with requests confirmed or denied as the recipients saw fit (referred to as “friending”). Access to all content on a profile page was restricted to confirmed “friends.” Summary information pertaining to the activities of “friends” was presented via a news feed on individual homepages. In addition, the website included a discussion forum, in which participants could ask questions, provide support, seek advice, and discuss ideas and thoughts with the community at large. However, this study found inclusion of social networking features in an online weight loss program did not significantly affect participants’ weight loss or retention, as compared with a basic informational website.

In contrast to Brindal et al.’s multifaceted SNS design for weight loss, Centola’s (2010, 2011) design did not involve many conventional SNS elements. Participants still created their own profiles, but instead of allowing participants to identify their connections, the researcher constructed the network connections for them. Participants recruited online were randomly assigned to different social networks with fixed structures, which then determined participants’ network connections (referred to “online buddies”). On the study website, participants could see their buddies’ profiles and activity
information. When a participant started a new activity, his or her buddies were notified about the new activity and were invited to also adopt it. The first experiment compared the effects of random networks (i.e., each node connects randomly to other nodes in the network) with clustered-lattice networks (i.e., each node connects to all of its nearest neighbors in the network) (Centola, 2010). The second experiment compared the effects of homophilous clustered-lattice networks (i.e., each node connects to all of its nearest neighbors who share similar characteristics) with nonhomophilous clustered-lattice networks (i.e., each node connects to all of its nearest neighbors who do not share similar characteristics) (Centola, 2011). The outcome was a binary behavior, signing up for an online diet diary tool. Each experiment found that clustering – individuals in a network sharing neighbors, and homophily – similarity of neighbors (manipulated based on gender, age, and self-reported body mass index [BMI]) in constructed online social networks contributed to the diffusion of signing up for an online diet diary tool. In other words, when participants in the online social networks saw several other participants who were similar to them regarding gender, age, and BMI signed up for the online tool, they were more likely to sign up for the online tool themselves in comparison with participants in the control group who saw dissimilar others. Importantly, moderation analyses showed obese participants benefited more from the homophily treatment than did non-obese participants. More obese participants adopted the online tool when they saw other obese buddies adopted it. Centola’s experiment approach demonstrates innovative ways to design online social networks and arrange the social connections within. Although the two experiments found significant effects on adopting an online tool, it remains to be
demonstrated that the same mechanism can apply to more effortful health behaviors (e.g., exercising, weight loss, smoking cessation).

Summarizing previous research, currently there is no standard design protocol or template for online social network health interventions. Most interventions combined the social network component with other commonly used online behavior change techniques such as goal-setting and personalized feedback, which makes it impossible to attribute outcomes to specific intervention components (Vandelanotte et al., 2016). Two meta-analyses did not identify effects of online social network interventions on health behavior change (Laranjo et al., 2015; Maher et al., 2014). Maher and colleagues (2014) found effect sizes for behavior change ranged widely and were non-significant in general based on 10 studies (Cohen’s d −0.05, 95% CI [0.45-0.35] to 0.84, 95% CI [0.49-1.19]). Although Laranjo and colleagues (2014) found a small positive effect based on 12 studies (Hedges’ g 0.24, 95% CI [0.04-0.43]), it is important to note that after dropping the two studies by Centola (2010, 2011), the effect dropped to 0.05 and became non-significant.

Many online social network interventions are based on theoretical mechanisms that operate in offline social network interventions, such as providing social support or social influence. However, it is not clear what the unique advantages of using online social networks are. Researchers often assume putting people (whether friends or strangers) into online social networks would trigger social support or social influence processes, but no previous study examined the hypothesized mechanisms in relation to specific online social network features. Cavallo et al. (2012) examined perceived social support as a result of the Facebook intervention. Although the study found an overall increase in perceived social support throughout the program, the effects of the multi-
component intervention and the control condition (i.e., informational website) were not
different. It is unclear whether the observed effects in this multi-component intervention
were attributable to the online social networks, the non-network components, or a
synergistic effect of both. Thus, factorial experiment design or mediation analysis should
be considered more often, so that the efficacy of online social networks for behavior
change can be clearly evaluated.
CHAPTER 3
THEORETICAL FRAMEWORKS

Few studies used behavior change theories to guide online social network intervention design. Three studies utilized social cognitive theory (Mayer & Harrison, 2012; Turner-McGrievy & Tate, 2011; Valle, Tate, Mayer, Allicock, & Cai, 2013) and one study applied the theory of planned behavior in analyzing the results (Brindal et al., 2012). In this chapter, I discuss three important theoretical frameworks that guide the design and analysis of the present research.

Berkman’s Conceptual Model of Social Networks and Health

Berkman et al. (2000) proposed a conceptual model of how social networks impact health. The model depicts a cascading causal process beginning with the macro-level social structural conditions to mezzo-level social networks and then to micro-level psychobiological mechanisms that are dynamically linked to impact health behaviors and outcomes (see Figure 3.1). Social networks are conditioned upon specific social structures (e.g., culture, socioeconomic factors, politics). Social network-level factors include structural (e.g., size, density, homogeneity, centrality) and tie characteristics (e.g., reciprocity, intimacy, duration). Psychosocial mechanisms include social support (e.g., emotional, informational, appraisal, instrumental support), social influence (e.g., norms, imitation, social comparison), social engagement and attachment (e.g., church attendance, community belonging), person – to – person contacts (e.g., pathogen exposure), and access to resources (e.g., money, foods, jobs, information). Individual-level health
determinants refer to specific health behaviors (e.g., smoking, drug use, physical activity) and physiological pathways (e.g., immune system function).

Figure 3.1. Berkman’s Conceptual Model of Social Networks and Health

(source: Berkman et al., 2000)

One important feature of the model is that it considers the upstream factors such as culture and politics that condition the formation and characteristics of social networks. This directs research attention to identifying and intervening on social infrastructures that shape social networks. For instance, studies have identified the contribution of local parks to the development of social ties in inner-city neighborhoods (Kazmierczak, 2013). On the contrary, less green space in people’s living environment coincided with feelings of loneliness and perceived shortage of social support, which then led to poorer self-reported health (Maas, van Dillen, Verheij, & Groenewegen, 2009). When the model was
proposed in 2000, social media or SNSs were still in their infancy. Berkman and colleagues did not include technological changes in the model or envision the impact of the Internet and SNSs on health. Given the increasing range of social functions of online networks, researchers should now consider the evolution of social networking technology as one factor under social change that directly conditions and shapes our social network structures and tie characteristics. Studies have linked individuals’ use of popular SNSs to increasing social capital and psychological well-being (Ellison, Steinfield, & Lampe, 2007). However, no robust evidence exists regarding online networks’ contribution to health behavior change or improved health outcomes (Eysenbach, Powell, Englesakis, Rizo, & Stern, 2004). The gaps suggest that the relationships among online networks, social interactions, and health behaviors and outcomes have not been clearly conceptualized and rigorously examined.

If we add online social networks under the social-structural conditions, following the model’s logic, we should hypothesize that the design of SNSs determines social network structures and tie characteristics, which then gives rise to psychosocial mechanisms that impact on individual-level health determinants and health outcomes. For instance, if SNSs are specifically designed to encourage supportive communication regarding physical activity, such social interactions would potentially enhance companionship and esteem support, which then lead to increased levels of physical activity (Cavallo et al., 2014).
Integrative Model of Behavior Prediction

Integrative model of behavioral prediction (IMBP) (Fishbein & Ajzen, 2010), shown in Figure 3.2, is a more micro and precise model to conceptualize and analyze the effects of online social networks on health. The IMBP extends the earlier models including the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB) (Ajzen, 1991) and postulates that intention serves as the most immediate predictor of behavior. Behavioral intention is influenced by three factors: (1) Attitude, or the extent to which an individual perceives outcomes of a behavior to be desirable and likely, (2) perceived injunctive norm regarding important others’ approval of the behavior and perceived descriptive norm regarding whether one’s referent groups engage in the behavior, and (3) perceived behavioral control, or perceived confidence in personal abilities to correctly undertake the behavior, a concept similar to self-efficacy. Previous studies supported the predictive validity of the model in physical activity (Hagger, Chatzisarantis, & Biddle, 2002).

![Integrative Model of Behavior Prediction](source: Fishbein & Yzer, 2003)
One contribution of the IMBP is that it includes distal variables. The effects of distal variables on intention and behavior are theorized to be mediated through the more proximal determinants of intention (e.g., attitude, perceived injunctive and descriptive norms, and perceived behavioral control). Fishbein and Ajzen (2010) located media exposure within this category of distal variables. Online social networks can also be a distal variable that influences the psychological factors. Similar to the conceptualization of media effects, the contents and frequencies of online interactions become the distal variables that influence individuals’ attitude, perceived norms, and perceived behavioral control. The IMBP has been used extensively to guide the design of media messages to change behaviors through formative research that elicits the population-specific beliefs relevant to attitude, injunctive norm, descriptive norm, and perceived behavior control (Fishbein & Cappella, 2006). Previous individual-based interventions have identified attitude, injunctive norm, perceived behavioral control, and intention as mediators of physical activity interventions. Although descriptive norm was found to strongly predict behavior intention, it was not affected by such individual-level interventions (Jemmott, et al., 2015a; Jemmott et al., 2015b). Communication contents on online social networks can be designed to influence attitude, perceived injunctive norm, and behavior control. More importantly, online social networks can play a unique role in addressing perceived descriptive norm in intervention efforts, as it allows and facilitates continuous social interactions focusing on the target behavior. The dynamic changes of behavior and descriptive norm may further impact on individuals’ attitude, perceived injunctive norm, and behavior control.
Descriptive Social Norms

The descriptive norm describes what is typical or normal (Cialdini, 2008). Cialdini proposed that the tendency to follow others offers an information-processing advantage and a decisional shortcut when one is choosing how to behave in a given situation (Cialdini & Goldstein, 2004). There is a medium to strong correlation between descriptive norm and behavior intention. Convergent evidence also indicates that the relation between descriptive norm and behavior is stronger than the relation between injunctive norm and behavior and there is a significant direct relation between descriptive norm and behavior in the context of TPB (Manning, 2009; Rivis & Sheeran, 2003).

Cialdini and colleagues also developed the focus theory of normative conduct (Cialdini, Kallgren, & Reno, 1991; Cialdini, Reno, & Kallgren, 1990), which asserts that norms are only likely to influence behavior directly when they are focal in attention thus salient in consciousness. In order to induce norm-consistent behaviors, the target people need to be focused on normative considerations in specific contexts. Given this requirement, descriptive normative persuasion for behavior change faces the challenge of making the norm salient not only immediately following message reception, but also salient in recurring situations in the future as well. The long-term efficacy of normative persuasive communications thus largely depends on continuously accessible normative information over time. The classic technique used in descriptive normative persuasion is to direct people’s attention to other people who are doing the desirable behavior. For instance, on persuading people to reuse their towels, the message simply said “the majority of hotel guests do reuse their towels when asked” (Goldstein, Cialdini, & Griskevicius, 2008). On persuading office workers to get physically active, the message
said, “…most employees at your company are finding ways to be active when they can be…Studies have shown that 3 out of 4 men and women in office jobs choose to use the stairs instead of the elevator…” (Priebe & Spink, 2012). This type of short-term static persuasion can be effective, however, it may not be feasible for sustaining long-term behavior change.

Recent years have been marked by an increased interest in the dynamic processes that drive social influence on the group-level behavior and belief changes and consequences over time. Based on the dynamic social impact theory (DSIT) (Latane, 1996), an individual occupying a given social space will be more likely to conform to the attitudes, beliefs, and behavioral propensities exhibited by the local numerical majority than by either the local numerical minority or less proximate persons. Influence at the local levels may be informational, normative, or both. The self-reinforcing nature of local social networks tends to perpetuate the norms’ existence once they are formed. These predictions have been found in early experimental electronic networks for opinion conformity (Latane & Bourgeois, 1996; Latane & LHerrou, 1996) and in recent experimental online networks for norm formation (Centola & Baronchelli, 2015) and health behavior adoption (Centola, 2010, 2011).

Compared with the static normative persuasive messages that aim to directly change people’s perceived descriptive norms, online social networks are platforms that need to be designed to promote and sustain the desired norms in a dynamic manner, meaning individuals can observe other people’s gradual behavior change and update their normative beliefs accordingly. Although no prior study has explicitly discussed how to effectively design online social networks to achieve this goal, the following design
suggestions can be summarized based on experiments that compared effects of different network structures on social influence: (1) The greater the network clustering – individuals sharing overlapping neighbors and the greater the homogeneity – individuals are similar to each other in online social networks, the stronger normative influence will emerge. Accordingly, online social networks need to ensure each individual has overlapping neighbors (e.g., individuals in a small clique that everyone has connections with everyone else) and the networks are consisted of similar individuals (e.g., similar in age, gender, and body weight) (Centola, 2010, 2011); (2) the more individuals can relate to and interact with each other in online social networks, the stronger normative influence will emerge (Postmes, Spears, & Lea, 2000; Postmes, Spears, Sakhel, & de Groot, 2001). Accordingly, online social networks need to focus the target individual’s attention to other people’s healthy behaviors that researchers want to promote and continuously communicate to the target individual about other people’s healthy behaviors. Because behavior change takes time, it is possible that individuals observe others’ behavior change before they form new normative perceptions.

Summary

Berkman’s model of social networks and health provides a macro perspective to conceptualize the potential function of online social networks in impacting health behaviors and outcomes. The model suggests that online social networks can potentially condition people’s social interactions that lead to behavior changes through various psychological mechanisms. The IMBP examines the specific psychological determinants of behaviors and provides a predictive structural model to guide the design and analysis
of online social network interventions. Specifically, the IMBP can be utilized to conduct formative research to elicit important behavioral beliefs and to design belief-relevant intervention messages. One failure of IMBP-based individual-level intervention is that they could not change perceived descriptive norm because the intervention does not change participants’ network members’ behavior over time. Theories on descriptive norms highlight the important contribution of online social networks and suggest specific design features to maximize normative social influence. In the context of physical activity, online social networks can highlight similarities among individuals, enable normative comparisons of physical activity, and provide instantaneous behavioral cues and reinforcement. Furthermore, offline physical activities resulting from online interactions may stimulate online interactions that further promote offline activities. In this regard, physical activity behavior change can be first initiated through the offline traditional intervention based on the IMBP and the unique advantage of using online social networks is leveraging descriptive normative influence to continuously promote and sustain behavior change. In addition, a secondary advantage is enabling the provision of social support, as examined in previous online social network intervention research.
CHAPTER 4
INNOVATION

This dissertation’s chief innovation is exploring a novel approach to physical activity intervention, constructing online social networks to increase physical activity. It advances research methodology and application, shifting the focus from individual-level interventions to social network-level interventions. Social networks are particularly important in shaping descriptive norms because people construct normative beliefs based on their observations of others’ behaviors (Christakis & Fowler, 2007; Priebe & Spink, 2011). However, descriptive norms have been underappreciated as a source of behavior change both in theory and in practice (Cialdini, 2007; Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008). Online social networks give people the opportunity to connect with others and observe others’ behaviors through real-time updates, suggesting online social network interventions can change health behaviors. Most online social network interventions use existing social networking sites such as Facebook and Twitter as a means of providing education and delivering interventions (Laranjo et al., 2015), not considering the potential of purposefully constructing online social networks for behavior change through normative influence. However, two recent experiments constructed online social networks for behavior change (Centola, 2010, 2011), randomly assigning participants into networks. Participants in the networks received real-time web and email notifications about their network peers’ behaviors. The results showed that online social networks significantly increased signing up for an online diet diary tool.

Most research to date on online communities focused on the benefits of social support for coping with life-threatening diseases or severe conditions, such as cancer,
HIV/AIDS, and mental illness (Versey, 2014). Recently, attention has shifted to the possible use of social networking sites to promote health behaviors. Understanding how online social networks facilitate behavior change can bridge important gaps in the way technology can be used to intervene on health.

Building on the previous literature, this dissertation extends research on small group interventions and explores the feasibility and efficacy of online social network interventions. It tests the effects of constructed online social networks on participants’ physical activity and psychological mechanisms. Most previous research hypothesized that online social network interventions work through the provision of social support (Cavallo et al., 2014; Cavallo et al., 2012a; Eysenbach et al., 2004), hence, involving family members or close friends would boost intervention efficacy. However, this line of reasoning may have underestimated the utility of new social connections in expanding people’s social networks and constructing new descriptive norms. In other words, putting people in familiar groups for an intervention may be efficacious, but, more interestingly, putting people in online social networks with unfamiliar others may also be efficacious, for people in such networks can connect with others who they did not previously know and receive updates on those people’s behaviors, which may foster the descriptive normative belief that other people are exercising.

To be sure, a study by Wing and Jeffery (Wing & Jeffery, 1999) found that enrolling participants age 25 to 55 years with their friends together into a weight-loss intervention resulted in greater weight loss than did enrolling participants without their friends. However, another study (Kumanyika et al., 2009) found no effect of participating with family members and friends on weight loss among African American women. The
only exception was that enrolling with partners was associated with greater weight loss when the family members and friends attended more intervention sessions or lost more weight. Similarly, a study on a predominantly White sample found that post-intervention weight loss was associated with having a study partner who lost weight (Gorin et al., 2005). None of these studies randomly assigned participants to enroll with friends or alone; hence, causal conclusions about the effects of involving the participants’ social networks cannot be drawn based on these studies. None of these studies focused on physical activity or reported data on theoretical variables that might mediate behavior change.

This dissertation addresses these issues using a novel research design. Individuals enrolled in the study are randomized to different network conditions. This methodology puts individuals who do not know each other beforehand into researcher-constructed online social networks. Thus, we construct participants’ social networks for them to interact with one another while simultaneously randomizing participants’ characteristics at baseline across conditions. This new approach may accelerate public health research focusing on designing and testing online social network interventions and social media-based health programs in general. Based on the theoretical discussions, this dissertation examines whether online social network physical activity intervention will increase physical activity compared with the no-online social network condition, whether online social network physical activity intervention will change the IMBP theoretical variables, especially perceived descriptive norm, compared with the no-online social network condition.
CHAPTER 5

EFFICACY OF WEB-BASED ONLINE SOCIAL NETWORK INTERVENTIONS TO INCREASE PHYSICAL ACTIVITY (STUDY 1 & 2)

Abstract

To identify the efficacy of web-based online social network interventions to increase physical activity, two field experiments were conducted at a large Northeastern university in Philadelphia, PA. In the first RCT, 217 graduate students were randomized to three conditions: a control condition with a basic online program for enrolling in exercise classes for 13 weeks, a media condition that supplemented the basic program with online promotional media messages that encourage physical activity, and a social condition that replaced the media content with an online network of 4 to 6 anonymous peers composed of other participants of the program, in which each participant was able to see their online peers’ progress in enrolling in classes. The primary outcome was exercise class enrollment. The study revealed that compared with the control condition, the media condition did not significantly increase participants’ exercise class enrollment, while online networks of the social condition significantly increased exercise class enrollment. In the second RCT, using the same program structure, 790 graduate students were randomized to four conditions comparing the effects of competitive interactions versus supportive interactions and individual versus team incentives in increasing exercise class attendance (i.e., control, social comparison, social support, and combined). The primary outcome was exercise class attendance. The control condition, also the individual alone condition, was used to enroll in exercise classes. The social comparison condition placed participants into 6-person competitive networks with individual
incentives. The social support condition placed participants onto 6-person teams with collective incentives. Participants could interact with and encourage team members. The combined condition was identical to the support condition, except that participants could compare their team’s performance to 5 other teams’ performances. Results showed attendance rates were 85% higher in the social comparison and the combined conditions in contrast to the two conditions without social comparison. The social support condition did not affect attendance as compared with the control condition. Social comparison was more effective for increasing class attendance than social support. Social comparison effects were equally strong regardless of whether it was based on individual or collective incentives. These two studies demonstrate the feasibility and efficacy of online social network interventions deployed through websites tailored to specific research questions.
Introduction

Improved technologies make online social networks a promising intervention platform for increasing physical activity (Centola, 2013; Chou, Prestin, Lyons, & Wen, 2013; Kreps & Neuhauser, 2010). Although health providers and entrepreneurs have attempted to use online social networks for promoting health and fitness (Bennett & Glasgow, 2009; Chou et al., 2013; Korda & Itani, 2013; Li et al., 2013; Young, Rivers, & Lewis, 2014), recent meta-analyses have provided mixed support for their effectiveness (Laranjo et al., 2015; Maher et al., 2014). Little is known about whether or how these technologies can be used to design a cost-effective solution for sedentary lifestyles.

Study 1 aims to establish the efficacy of online social network intervention and presents results from a RCT that evaluated two prominent strategies for conducting physical activity interventions: media campaigns that use professionally produced messages to improve exercise habits (Kroeze, Werkman, & Brug, 2006; Mozaffarian et al., 2012; Williams & French, 2011) and social networks that provide information about the behavior of other members in the online program (Centola, 2010, 2011). Promotional messages have been argued to be effective intervention strategies (Bennett & Glasgow, 2009; Cassell, Jackson, & Cheuvront, 1998). In particular, multimedia health campaigns that combine visual and audio components in a high arousal format have been effective for increasing responsiveness (Houts, Doak, Doak, & Loscalzo, 2006; Kang, Cappella, & Fishbein, 2006). Less is known, however, about how online social networks might impact physical activity. Effects of social influence on health behaviors and outcomes have been documented (Christakis & Fowler, 2013). Recent studies suggest that online networks may be effective for increasing fitness among social media users through elevating social
influence (Centola, 2013). However, it is difficult to evaluate the causal effects of social networks on physical activity in previous RCTs because they typically combined multiple strategies such as health education, peer interaction, and motivational messaging into a single treatment (Cavallo et al., 2012; Napolitano, Hayes, Bennett, Ives, & Foster, 2013; Neiger et al., 2012), making it impossible to identify a specific mechanism directly associated with improved activity.

Study 2 delves into the social influence mechanisms and aims to compare the effects of supportive versus competitive motivations. Social support is one of the most widely used and studied strategies for encouraging behavior change in social networks (Berkman & Syme, 1979; House et al., 1988). When people with similar interests interact to achieve a shared goal, social support can reduce the perceived costs of adopting a new exercise routine by providing companionship in the activity (Cavallo et al., 2014; Uchino, 2006). Further, social support may reduce the uncertainty of exploring new exercises by providing access to relevant sources of peer information. Thus, cooperative online relationships, where people work towards the same health goals, can foster collective efficacy for improving everyone’s levels of physical activity (Cohen, Finch, Bower, & Sastry, 2006). While social support is fostered through cooperative relationships, an alternative approach to promote physical activity is through competitive social relations (Foster, Linehan, Kirman, Lawson, & James, 2010; Zhang, Brackbill, Yang, & Centola, 2015). Social comparison strategies are implicit in fitness and exercise programs that use rankings, leader boards, and social status markers to increase physical activity. In these competitive environments, people work towards their goals individually, and differences in goal attainment motivate individuals to adjust their aspirations upward (Festinger,
1954). The dynamic process of comparing oneself to others increases everyone’s expectation for goal attainment and eventually improves overall levels of physical activity (Leahey, Kumar, Weinberg, & Wing, 2012; Shakya, Christakis, & Fowler, 2015). This study evaluates the effects of each of these approaches independently, and in combination, to determine how social motivations elicited through online social networks directly impact people’s exercise activity.

Program Infrastructure

The two studies were built on the same fitness program infrastructure: a semester-long program called SHAPE-UP at a northeastern university. The program offered workout classes to assist participants in establishing exercise routines. Class content covered both aerobic and muscle-strengthening physical activities, including running, spinning, yoga, Pilates, weight lifting, high intensity interval training, and group exercising. Each class lasted for an hour and was typically scheduled in the evening. Participants attending the class worked out for an hour with the instructor. The size of the classes varied depending on the class enrollment. Classes were led by instructors from the Department of Recreation and Health Services (DRHS) of the university. Participation in all classes was restricted to the program participants.

The SHAPE-UP website was designed for participants to enroll in classes and to interact with the program. To use the website, each participant created an anonymous online profile. All participants had continuous and equal access to the website. Classes were pre-programmed into an online calendar. Upon clicking a class, participants could read a description and register for it. The registration then triggered a confirmation email
that was immediately sent to the participant and a reminder email 12 hours before the class started. In addition, an online tracking tool allowed participants to keep a daily journal of their class completion. Upon using the website for the first time, participants were randomly assigned to experimental conditions.

Study Population

Participants were recruited through advertisements on the university’s website, the student email list, and the Facebook page of a graduate student organization. In addition, flyers were put up on billboards in campus buildings. Recruitment materials specified the purpose of the project was to improve the quality of student life by encouraging physical activity. Graduate students enrolled at the university who were older than 18 years of age and who logged into the program website at least once after creating online profiles were eligible. Eligibility was determined by an initial physical assessment conducted by the DRHS. Each participant first completed a screening questionnaire (Canadian Society for Exercise Physiology, 2002) designed to identify adults for whom physical activity might be inappropriate, then completed a pushup test, a sit-and-reach test, and a 3-minute step test according to the YMCA fitness test (Franks & YMCA of the USA., 1989). The assessment lasted for 10 minutes and the DRHS staff measured participants’ heights and weights for calculating the Body Mass Index (BMI) (National Heart Lung and Blood Institute & National Institute of Diabetes and Digestive and Kidney Diseases, 1998). In addition, participants completed a brief online survey that asked sociodemographic questions and the number of days on which participants reported engaging in 20 minutes of vigorous-intensity activity, 30 minutes of moderate-intensity
activity, and strength-building activity, in the past 7 days (Centers for Disease Control and Prevention, 2001). The 2008 physical activity guideline (Department of Health and Human Services, 2008) requires 20 minutes of vigorous-intensity activity on at least 4 days or 30 minutes of moderate-intensity activity on at least 5 days and engaging in strength-building activity on 2 or more days, in the past 7 days.

**Efficacy of Online Social Network Intervention (Study 1)**

**Method**

A 13-week online social network intervention was conducted at a northeastern university. The program offered 49 workout classes to assist participants in establishing exercise routines. On average, four classes were offered per week. Study 1 randomized participants to three experimental conditions: (1) The basic website (i.e., the control condition); (2) The basic website plus promotional media messages (i.e., the media condition); and (3) The basic website plus social network (i.e., the social condition). Figure 5.1 illustrates the three conditions of the experimental design.
Figure 5.1. Example webpage illustrations for the three experimental conditions in the trial.

The control condition provided participants with online tools for enrolling in classes and recording their progress. The media condition supplemented the basic tools with promotional media messages, including: two high arousal videos encouraging physical activity and one infographic with exercise tips and motivational messages on a weekly basis. The social condition supplemented the basic website with a network of 4 to 6 anonymous “peers” participating in the program. Social condition participants were able to see their peers’ profile information, including username, gender, age, school, as well as information about their peers’ progress and real-time notifications about their peers’ enrollment and completion of classes. These networks did not provide any additional incentives or content to promote physical activity, nor could participants directly communicate with their peers through the website. Thus, this experimental design identifies the independent effects of promotional media messaging and online networks in increasing physical activity.
Computer-generated random numbers were used to randomly assign participants to conditions. Participant enrollment and initial assessments were conducted from January 15, 2014 through February 1, 2014. Eligible participants completed a baseline online survey assessing demographic information and self-reported physical activity. Class instructors were blind to group assignments. All participants logged into the website throughout the 13 weeks of a semester at least once. Data collection was completed by May 5, 2014. The study was approved by the institutional review board of the university, and all participants provided informed consent.

**Outcome Measure**

The outcome was the number of enrollments in exercise classes, which was recorded when participants digitally confirmed class registration.

**Statistical Analysis**

A power analysis was performed to calculate the sample size required to detect a significant effect of the two treatment conditions on the primary outcome, class enrollment. Assuming a two-tailed test, $\alpha = 0.05$, 20% attrition, and an effect size of Cohen’s $d = 0.6$ (Cavallo et al., 2012b; Foster, Linehan, Kirman, Lawson, & James, 2010; Valle et al., 2013), 55 participants were needed in each condition (44 after attrition) to ensure 80% power to detect a significant difference between treatment and control.

An analysis of variance was conducted first to examine the effects of the experimental conditions on the outcome. Because enrollment numbers were counts and departed significantly from a normal distribution, negative binomial regression model
was used to examine the effects of treatment conditions on individuals’ numbers of class enrollment. Following that, non-parametric Wilcoxon rank sum tests (two-tailed) (Efron, 1981; Gibbons, 1993) were used to examine the effects of the two treatment conditions on overall enrollment compared with the control condition.

Based on the distribution of enrollment numbers, we further created a binary variable indicating whether participants enrolled in at least 6 classes throughout the program. Logistic regression analyses were then conducted to examine whether the two treatment conditions increased enrollment in at least 6 classes in comparison with the control condition.

Finally, the cumulative enrollment numbers were summarized by each day and by each condition. Linear regression was conducted to examine the increasing rate of class enrollment by day for each of the three conditions. The regression model regressed the cumulative enrollment numbers onto day (continuous variable ranging from 1 to 91) for each condition. Z-tests were then used to compare the regression coefficients between conditions.

All analyses were performed using an intent-to-treat method with participants analyzed based on their intervention assignment, regardless of the number of classes enrolled. All analyses were conducted in Stata, version 13.1.

Results

A total of 281 graduate students signed up for the program and 217 logged into the website at least once, which qualified them to be enrolled. All 217 attended the
physical activity assessment and were enrolled in January 2014. Figure 5.2 shows the flow of participants from enrollment through condition allocation.

Figure 5.2. Flow diagram of participants through the trial.

Table 5.1 shows participants’ characteristics. There were no baseline gender, age, BMI, or physical activity level differences between participants across conditions. Participants ranged in age from 21 to 51 years (mean = 25.8, SD = 4.0) and ranged in BMI from 16.4 to 38.8 (mean = 23.9, SD = 4.4). Among all, 22.6% were overweight, 10.6% were obese, and only 17.1% met physical activity guideline in the past 7 days.
Table 5.1: Baseline demographic characteristics of participating graduate students by experimental condition.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Media</th>
<th>Social</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (N)</td>
<td>75</td>
<td>69</td>
<td>73</td>
<td>217</td>
</tr>
<tr>
<td>Age (years; M [SD])</td>
<td>26.8 (4.8)</td>
<td>25.4 (3.6)</td>
<td>25.1 (3.1)</td>
<td>25.8 (4.0)</td>
</tr>
<tr>
<td>Male sex (%)</td>
<td>30.7</td>
<td>24.6</td>
<td>31.5</td>
<td>29.0</td>
</tr>
<tr>
<td>Body Mass Index (kg/m²; M [SD])</td>
<td>23.5 (4.1)</td>
<td>23.8 (4.4)</td>
<td>24.5 (4.7)</td>
<td>23.9 (4.4)</td>
</tr>
<tr>
<td>Overweight (BMI [25.0 – 29.9]; N[%])</td>
<td>19 (25.3)</td>
<td>17 (24.6)</td>
<td>13 (17.8)</td>
<td>49 (22.6)</td>
</tr>
<tr>
<td>Obese (BMI ≥ 30; N[%])</td>
<td>5 (6.7)</td>
<td>6 (8.7)</td>
<td>12 (16.4)</td>
<td>23 (10.6)</td>
</tr>
<tr>
<td>Met physical activity guideline in the past 7 days (N [%])</td>
<td>11 (14.7)</td>
<td>11 (15.9)</td>
<td>15 (20.6)</td>
<td>37 (17.1)</td>
</tr>
<tr>
<td>Moderate exercise in the past 7 days (days; M [SD])</td>
<td>2.2 (2.1)</td>
<td>2.0 (2.2)</td>
<td>1.8 (2.2)</td>
<td>2.0 (2.2)</td>
</tr>
<tr>
<td>Intensive exercise in the past 7 days (days; M [SD])</td>
<td>1.7 (1.6)</td>
<td>1.9 (2.0)</td>
<td>1.8 (1.8)</td>
<td>1.8 (1.8)</td>
</tr>
<tr>
<td>Strength exercise in the past 7 days (days; M [SD])</td>
<td>1.3 (1.5)</td>
<td>1.2 (1.6)</td>
<td>1.3 (1.7)</td>
<td>1.3 (1.6)</td>
</tr>
</tbody>
</table>

Note: No significant differences on all variables at baseline across conditions.

Data from all 217 participants were used for analyses on the outcome. All class enrollment counts were recorded digitally on the website so there was no missing data. The overall mean number of enrollments was 5.5 (SE = 0.5) throughout the program. The highest level of enrollment occurred in the social condition (mean = 6.3, SE = 0.9), followed by the media condition (mean = 5.7, SE = 1.1), and the control (mean = 4.5, SE = 0.9). However, analysis of variance on the mean numbers of class enrollment across the three conditions showed no significant difference (F [2, 214] = 1.05, p = 0.351). Pairwise comparisons also did not reveal any significant difference. The difference between the media and the control conditions was not significant (F [1, 142] = 0.84, p = 0.362). The difference between the social and the control conditions was not significant (F [1, 146] = 2.21, p = 0.139). The difference between the social and the media conditions was not
significant (F [1, 140] = 0.20, p = 0.652). In addition, the negative binomial model showed no significant effects of the treatment conditions.

Figure 5.3 shows the distribution of enrollment numbers across all quartiles for each experimental condition. The control condition had the largest fraction of participants in the first quartile (i.e., no enrollment). The media condition shifted the distribution of enrollment away from the lowest quartile, increasing the fraction of participants in the three upper enrollment quartiles by 18% as compared with the control condition (W = 5431, p = 0.08). However, overall class enrollment in the media condition was not significantly greater than the control condition. By contrast, in comparison with the control condition, social influence significantly produced a 167% (95% CI: 42% to 483%) increase in the fraction of participants above the 75th percentile of enrollment compared with the control condition (W = 6048, p = 0.02, r = 0.20).

Figure 5.3. Distribution of class enrollment across all quartiles by experimental condition.
Based on the results observed from the 75th percentile of enrollment, we further created a binary variable, enrollment in at least 6 classes, for each participant. Logistic regressions on this binary variable showed that the social condition significantly increased enrollment in at least 6 classes in comparison with both the media condition (Odds ratio = 2.39, 95% CI: 1.17, 4.89, p = 0.017) and the control condition (Odds ratio = 4.10, 95% CI: 1.89, 8.86, p < 0.0001). The media condition did not generate an increase in comparison with the control condition (Odds ratio = 1.72, 95% CI: 0.75, 3.92, p = 0.199).

In addition, the cumulative levels of enrollment in each experimental condition by day over the 13-week program were compared, as shown in Figure 5.4.

![Cumulative enrollment in exercise classes by day and experimental condition.](image)

In the first half of the program (i.e., through week 6), enrollment rates were significantly greater in both the media (6.42 per day, p = 0.001) and social conditions
(6.15 per day, p = 0.01), than in the control condition (5.16 per day). The social and media conditions showed no significant difference from one another (p = 0.48). However, during the second half, average enrollment rates in the media condition slowed considerably (3.55 per day), showing no significant difference from the control (3.26 per day) (p = 0.24). By contrast, average enrollment rates in the social condition remained elevated (5.22 per day) and were significantly greater than both the control (p < 0.001) and media condition (p < 0.001). While the effects of promotional messages and social influence were comparable at the beginning of the program, social influence was significantly more effective at creating sustained engagement.

Social Mechanisms of Online Social Network Intervention (Study 2)

Method

An 11-week online social network intervention was conducted at a northeastern university. The program offered 90 exercise classes. On average, eight classes were offered per week on the university campus. In a 2 by 2 factorial experiment, participants were randomized to four conditions: individual control, social comparison, social support, and combined conditions. Participants in the individual control condition were given the basic website interface, which could be used to look at the class schedule and register for classes. They were provided with no social incentives for participation and were rewarded at the end of the program based on their individual record of attendance at exercise classes. Three different experimental manipulations supplemented the control
condition by providing social incentives hypothesized to increase physical activity participation.

The *social comparison* condition supplemented the basic class registration website by giving participants access to 6-person online networks. Each participant in this condition was randomly assigned 5 exercise peers, which comprised 5 members of the study who were connected to the participant in a program-generated online social network. Participants in this condition were able to compare their performance in the program with their peers via a competitive ranking based on their peers’ exercise class attendance levels. As in the control condition, at the conclusion of the program, the rewards for participants were based on each participant’s individual record of class attendance. All network peers’ information was anonymous, and there was no possibility for direct communication between participants in this condition.

By contrast, the *social support* condition consisted of 6-person online social networks designed to provide participants with direct peer support from other members of the program who could encourage each other to improve their levels of regular exercise. Participants in this condition were randomly assigned to 6-person teams and rewards at the completion of the program were based on the team’s collective activity levels, incentivizing team members to actively support each other’s attendance at exercise classes. To facilitate supportive social interaction, participants in the social support condition were provided with a chatting tool that they could use to directly communicate with other team members in real-time. Team members could see both each other’s individual records of class attendance and the collective record of the team. They were
able to register for classes individually, but could also coordinate to register for classes collectively.

Finally, to understand if there was an interaction effect of combining the motivations of social support and social comparison, the *combined* condition randomly placed individuals on 6-person teams and provided the same team incentives and technologies as the social support condition plus a competitive feature, in the form of an interface that allowed participants to compare their team’s performance against the performances of 5 other teams. Figure 5.5 illustrates the four conditions of the experimental design.

![Figure 5.5](image)

Figure 5.5. Example webpage illustrations for the four experimental conditions in the trial.

*Outcome Measure*

The outcome of interest was the total number of exercise classes that participants attended throughout the 11-week program. Complete attendance data for all classes were provided by class instructors.
**Statistical Analysis**

A sample size of 688 was originally planned because 172 participants per randomization condition could achieve at least 90% power to detect a small to medium effect size of 0.35 (Cavallo et al., 2012a; Foster et al., 2010; J. Zhang et al., 2015) in class attendance difference at the 5% significance level.

The baseline analysis consisted of an analysis of variance to examine the effects of social support and social comparison factors on the outcome. In the social support, social comparison, and the combined conditions, individuals received the treatment as members of a network of 6 individuals, thus the primary analyses employed a multilevel negative binomial regression model to account for the clustering of the treatment within these groups. The multilevel model included the social support and the social comparison factors, the support × comparison interaction, and covariates of baseline demographics (i.e., age, gender, race, department, and having a gym membership in the previous semester).

Finally, the cumulative attendance numbers were summarized by each day and by each condition. Linear regression was conducted to examine the increasing rate of class attendance by day for each of the four conditions. The regression model regressed the cumulative attendance numbers onto day (continuous variable ranging from 1 to 77) for each condition. Z-tests was then used to compare the regression coefficients between conditions.

All analyses used the intention-to-treat principle (Shao & Zhong, 2003) and considered all participants who were randomly assigned to a condition. All analyses were conducted in Stata, version 13.1.
Results

Of the 1,007 participants who registered for the program, 790 attended the fitness evaluation, which qualified them to be enrolled in the program and be randomly assigned to a condition. Figure 5.6 shows the flow of participants from recruitment throughout the program. The experimental treatment was realized by exposure to the website. In total, 750 participants received at least one treatment exposure, as indicated by logging-in to the website. The attrition rates for participants receiving the treatment were statistically indistinguishable across all conditions, with 95% of all participants receiving the treatment.

![Flow diagram of participants through the trial.](image)

Table 5.2 shows participants’ characteristics. There were no significant differences in gender, age, race, or BMI between participants across conditions. Participants ranged in age from 20 to 59 years (mean = 25.2, SD = 3.4), and ranged in
BMI from 16.1 to 45.0 (mean = 23.0, SD = 3.8). Among all, 15.7% were overweight and 5.3% were obese.

Table 5.2: Baseline demographic characteristics of participating graduate students per experimental condition.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Support</th>
<th>Comparison</th>
<th>Combined</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (N)</td>
<td>202</td>
<td>192</td>
<td>198</td>
<td>198</td>
<td>790</td>
</tr>
<tr>
<td>Age (years; M [SD])</td>
<td>25.0 [2.7]</td>
<td>25.4 [3.5]</td>
<td>25.3 [3.8]</td>
<td>25.1 [3.5]</td>
<td>25.2 [3.4]</td>
</tr>
<tr>
<td>Male sex (%)</td>
<td>27.2</td>
<td>26.5</td>
<td>28.3</td>
<td>21.7</td>
<td>25.9</td>
</tr>
<tr>
<td>Race (N [%])</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>85 [42.1]</td>
<td>80 [41.7]</td>
<td>96 [48.5]</td>
<td>73 [36.9]</td>
<td>334 [42.3]</td>
</tr>
<tr>
<td>Body Mass Index (kg/m²; M [SD])</td>
<td>22.9 [4.0]</td>
<td>22.8 [3.6]</td>
<td>23.4 [3.8]</td>
<td>22.9 [3.7]</td>
<td>23.0 [3.8]</td>
</tr>
</tbody>
</table>

Notes: No significant differences on all variables at baseline across conditions.

Data from 790 participants were used for the analyses. The outcome was the number of exercise classes that participants attended, which ranged from 0 to 39 classes. Both the social comparison and the combined condition showed significant increases in exercise class attendance compared with the social support condition and the control condition. Social support did not produce any significant improvement in attending exercise classes above the control condition. As shown in Figure 5.7, attendance rates
were 85% higher in the social comparison and the combined conditions (mean = 1.9, SE = 0.2) compared with the two conditions without social comparison (mean = 1.0, SE = 0.2). Both the social comparison and the combined conditions had significantly higher mean attendance rates (mean = 1.9, SE = 0.3 and mean = 1.9, SE = 0.2, respectively) than the control (mean = 1.1, SE = 0.3), while social support performed worse (mean = 0.9, SE = 0.2). An analysis of variance showed that the presence of social comparison significantly increased activity levels (F [1, 788] = 8.96, p = 0.003, Cohen’s d = 0.21). In contrast, the presence of social support did not significantly affect participants’ exercise levels (F [1, 788] = 0.04, p = 0.85, Cohen’s d = 0.01). There was no interaction between the two factors (F [1, 786] = 0.18, p = 0.67).

![Figure 5.7. Mean exercise class attendance levels by experimental conditions.](image)

Table 5.3 presents results of the multilevel models that accounted for network-level influences within the network conditions. On average, social comparison increased
attendance rates by 128% (p = 0.016). After adjusting for baseline covariates, social comparison increased attendances by 99% (p = 0.005). In contrast, social support had no significant effect (p = 0.869). Additionally, the non-significant interaction between support and comparison suggests that social support did not contribute to the increased attendance rates in the combined condition. The success of the combined condition can be thus attributed to the effects of team-based social comparison.

Table 5.3. Multilevel models for the effects of experimental factors on exercise class attendance, Philadelphia, PA, 2014.

<table>
<thead>
<tr>
<th></th>
<th>Unadjusted for covariates</th>
<th>Adjusted for covariates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(n=790)</td>
<td>(n=789)</td>
</tr>
<tr>
<td>IRR (95% CI)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Comparison</td>
<td>2.28 (1.16, 4.47)</td>
<td>1.99 (1.18, 3.34)</td>
</tr>
<tr>
<td>Support</td>
<td>0.94 (0.47, 1.88)</td>
<td>0.67 (0.38, 1.16)</td>
</tr>
<tr>
<td>Comparison × Support</td>
<td>0.85 (0.31, 2.29)</td>
<td>1.00 (0.48, 2.08)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.73 (0.44, 1.21)</td>
<td>0.03 (0.002, 0.87)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1060.4632</td>
<td>-1022.869</td>
</tr>
<tr>
<td>Wald chi2 (3)</td>
<td>9.17</td>
<td>106.58</td>
</tr>
<tr>
<td>(p= 0.0271)</td>
<td></td>
<td>(p&lt;.0001)</td>
</tr>
</tbody>
</table>

Notes: a Covariates included age, gender, race, department, and having a gym membership in the previous semester.

b The difference in sample sizes arises from one missing data point for age.

c Boldface indicates statistical significance.

Comparing the experimental network conditions with the control condition showed similar results. Specifically, after adjusting for baseline covariates, the social
comparison condition increased attendance rates by 99% (p = 0.01) in comparison with the individual control condition. The team comparison condition increased attendance rates by 33% (p = 0.078) in comparison with the control, approaching statistical significance. In contrast, the social support condition did not change attendance (p = 0.869). Exercise class attendance rates were similar among network peers in the two effective network conditions involving social comparison. The intraclass correlation was 0.12 (95% CI: 0.04, 0.22) for the social comparison networks, and was 0.21 (95% CI: 0.09, 0.38) for the team comparison networks. In contrast, the intraclass correlation was 0.07 (95% CI: -0.02, 0.21) and not significant for the social support networks.

Figure 5.8 plots cumulative class attendances by day in each condition. Both of the conditions with social comparison (i.e., comparison and combined) showed significantly higher levels of attendance each day, averaging 5.1 and 5.5 participants attending exercise classes per day, respectively. Both were significantly higher than the average of 2.9 attendances per day (p < 0.001) in the control condition. Class attendance in the support condition grew at a significantly slower rate than in the control condition, averaging only 2.4 attendances per day (p < 0.001), suggesting that social support might have reduced daily exercise rates as compared to the control condition. The increasing rates for the social comparison, the combined, and the social support conditions did not significantly differ between the first half (i.e., through week 6) and the second half of the program. However, the increasing rate for the control condition was significantly slower in the second half than in the first half of the program, averaging 3.4 and 2.3 exercise class attendances per day, respectively (p < 0.001).
Figure 5.8. Cumulative attendance at exercise classes in each of the four conditions.

**General Discussion**

These two field RCTs report findings on the efficacy of web-based online social network interventions and confirm that online social networks can increase physical activity compared with the no-online social network conditions. Specific communication design features of online networks can further elicit different social interaction and influence mechanisms that make some networks more effective than others in increasing physical activity.

Study 1 randomized 217 graduate students to three conditions (i.e., control, media, and online social network). Nonparametric tests found that compared with the control condition, media messages did not increase overall exercise class enrollment, while online networks with 4 to 6 anonymous peers significantly increased enrollment among the most active participants. Online social networks significantly increased
enrollment in at least 6 classes in comparison with both the media condition and the control condition. Study 2 extended Study 1 and greatly improved the design. While the outcome in Study 1 was a digital behavior, signing up for an exercise class online, the outcome in Study 2 became behavioral, actually attending an exercise class and working out for an hour. Study 2 randomized 790 graduate students to four conditions (i.e., control, comparison, support, and combined) and found significant differences on individual class attendance. Class attendance rates were 85% higher in the social comparison and the combined conditions than in the two conditions without social comparison. Social comparison was more effective for increasing class attendance than social support. Interestingly, social comparison effects were equally strong regardless of whether it was based on individual or collective incentives.

In these two studies, through online social networks, real-time signals about peers’ exercise behaviors constituted the main form of social influence. As participants start to exercise, their exercise behavior signals get broadcasted to their network peers in real time through both emails and the website. Behavior signals get continuously updated and communicated within the network, dynamically forming a reinforcing loop that motivates everyone in the network to keep exercising. Because the signals are always about exercising, they focus the network members’ attention to their peers’ positive behaviors, which may have helped to form a shared normative perception that others are making effort to increase their activity levels. Compared to the approach that uses aggregate statistics to shape normative perceptions (Cialdini, 2007; Cialdini & Goldstein, 2004), this network approach enables dynamic formation and consolidation of descriptive norms based on real behavior observations.
The methodological approach demonstrates an important innovation over traditional web-based intervention studies that rely on using existing online applications to study behavior change. While traditional methods cannot provide a clear identification of the effects of online networks on behavior change, this approach allows constructing online social networks in which researchers control all of the informational and social signals within the networks (Centola, 2013). Referring back to Berkman’s conceptual model, both Study 1 and 2 constructed online networks and manipulated the characteristics of online network ties. Specifically, they pushed behavior signals automatically through the network ties. Study 2 further built on Study 1 and designed the social networks to elicit different social influence mechanisms. Simply by reframing the functions (e.g., competitive or supportive networks) without manipulating network structures, different networks generated different levels of behavior change.

While this experimental approach offered several methodological advantages, including the ability to create controlled networks and the capacity to identify the causal mechanisms through which network tie characteristics directly impact health behaviors, these two studies also come with limitations. Most notably, the two studies focused on graduate students, who are typically less at health risk than other segments of the broader population. In future work, the experimental design could be extended to study other behaviors that may be more broadly applicable outside a university facility, such as running, walking, or complying with prescribed medications. A second limitation is that the outcomes were signing up and attending exercise classes arranged by the university, which may not translate into participants’ daily exercise activities or clinical significant results such as BMI change and muscle strength change. Future studies would benefit
from using fitness trackers to get continuous behavioral measures on exercise intensity and time spent in exercises. Finally, while the studies focused on the effects of online social networks on exercise class participation, they did not rigorously measure theoretically variables that can explain the psychological mechanisms underlying the network effects. Additional studies are required to provide deeper insight into the mediation mechanisms, namely, the indirect effects of online social networks on behavior change through changes in participants’ subjective evaluations of their psychological states and their social surroundings. Future work would also benefit from extending these studies to include long-term follow-up data on participants’ continued engagement with exercises after the intervention. While these limitations provide useful directions for future work, the approach offers an important step forward for using in vivo experimental designs for identifying the effects of online social networks on health behaviors.
CHAPTER 6

EFFICACY OF MOBILE-BASED ONLINE SOCIAL NETWORK INTERVENTION TO INCREASE PHYSICAL ACTIVITY AMONG YOUNG AFRICAN AMERICAN WOMEN (STUDY 3)

Abstract

Significant weight gain and physical inactivity happen during early to mid-twenties, with young African American women experiencing the greatest weight gain among all racial and gender groups. Many theories support the view that social networks affect health behaviors. A few studies have tested interventions targeting social networks, but none has tested the effects of such interventions on African American women’s physical activity. This study aimed to test the efficacy and mediation of a mobile app based online social network physical activity intervention for African American women age 18 to 35 years. In a RCT, participants were randomized to the online social network condition or the control condition. All participants received a Fitbit physical activity tracking device and an introductory physical activity promotion session emphasizing the health benefits of physical activity and building skills for daily exercises. Participants in the control condition used the PennFit app to record and monitor their own physical activity progress. Participants in the online social network condition were randomized to 4-women networks and were able to see and compare their own recorded physical activities with activities of the other three women in their network. In addition, participants in the online network had access to an instant chatting tool to chat with one another. The primary outcome was daily active exercise minutes. Results showed the online network condition did not impact daily active minutes in comparison with the control condition during the 30-day program. All participants increased their self-
reported physical activity after the program and the online networks increased engagement with the Fitbit device and the PennFit app in comparison with the control condition.

Introduction

Some of the largest health disparities in the U.S. concern African American women, who have disproportionately high morbidity and mortality rates from chronic diseases, including heart disease, stroke, hypertension, type-2 diabetes, and cancer (American Cancer Society, 2013; Centers for Disease Control and Prevention, 2011; Go et al., 2013; Murphy, Xu, & Kochanek, 2013). Physical activity is associated with reduced morbidity and mortality from chronic diseases (Lee, Rexrode, Cook, Manson, & Buring, 2001; Sattelmair et al., 2011) as well as reduced all-cause mortality (Koring et al., 2012; Oguma et al., 2002; Samitz et al., 2011; Wen et al., 2011). Although physical inactivity is common among women regardless of race, the prevalence was much higher in African American women than in White women. Only 10.8% of African American women met the national guidelines for both aerobic and muscle-strengthening physical activity in 2012, compared with 19.9% of White women (National Center for Health Statistics, 2014). Paralleling this is the high rate of obesity in African American women: 40.9% of African American women compared with 26.2% of White women were obese in 2012 (National Center for Health Statistics, 2014). Most weight gain occurs before middle age (Williamson, Kahn, Remington, & Anda, 1990), and young African American women experience the greatest weight gain among all racial and gender groups (Burke et al., 1996; Rosenberg, Kipping-Ruane, Boggs, & Palmer, 2013). Furthermore, physical
inactivity habits developed in younger ages are likely to continue into later life (Kvaavik et al., 2003), which underscores the urgent need for interventions to encourage greater physical activity among young African American women.

Despite the racial disparities in rates of chronic diseases and behaviors linked to chronic diseases, there have been relatively few RCTs of interventions to increase physical activity in African American women (Lemacks, Wells, Ilich, & Ralston, 2013; Yancey et al., 2004). Although some studies found significant improvement on physical activity, most focused on individuals and did not take into consideration the social contexts in which the participants’ behaviors occurred. A review of qualitative studies of physical-activity correlates in African American adults found that both men and women said group participation would increase their motivation to exercise, and women said that having a physically active partner or friend would facilitate their initiation and maintenance of a physical-activity program (Siddiqi, Tiro, & Shuval, 2011). For instance, focus groups with African American women suggested that having a friend or group to exercise with was motivating and should be considered to be an important component of physical activity programs (Young, He, Harris, & Mabry, 2002). This finding is consistent with other studies identifying social support as encouraging African American women to engage in physical activity (Harley et al., 2009; Komar-Samardzija, Braun, Keithley, & Quinn, 2012).

While previous research emphasized the effects of social support on facilitating physical activity, it is also possible that a lack of social network members perceiving physical activity as a normative behavior may contribute to low rates of physical activity in African American women. Two correlational research found that social support and
descriptive norms both predicted physical activity independently (Ball, Jeffery, Abbott, McNaughton, & Crawford, 2010; Okun et al., 2003). Two experiments found that manipulating descriptive norms increased physical activity (Priebe & Spink, 2012, 2014). The findings suggest creating physical activity as a normative behavior within African American women’s social networks may be an effective way to establish, potentially sustaining physical activity in the long term.

Young African Americans are heavy users of social networking technologies. In 2013, 96% of African Americans aged 18 to 29 used a social networking site of some kind (Fox & Duggan, 2013). Understanding how online social networks facilitate behavior change can bridge important gaps in the way technology can be used to intervene on health among underserved populations (Versey, 2014). The primary objective of this study was to test the efficacy of a mobile app (PennFit) intervention in increasing participants’ daily active minutes objectively recorded by a fitness tracking device (Fitbit zip). In the control group, participants used the PennFit app to record and monitor their own physical activity progress. In the online social network intervention, participants were randomized to 4-women networks and were able to see and compare their own recorded physical activities with activities of the other three women in their network. Participants in a network had access to an online chatting tool to chat with one another. The secondary objective was to understand the intervention’s mechanisms through mediation analysis on theoretical variables. Mediation analysis (Baron & Kenny, 1986; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002) can help examining an intervention-efficacy trial by identifying which theoretical variables are most effective or not effective for changing physical activity-related behaviors.
Method

Design Overview

The overall strategy included using formative research to inform the mobile app intervention development and a RCT design to test the preliminary efficacy and mediation of an online social network intervention in comparison with a control condition where participants used the mobile app on their own. A one-month RCT was conducted. A total of 91 participants gave their informed consent and were randomly assigned to the control condition or the online network intervention condition. Participants completed assessments before and one month after using the PennFit mobile app. All participants received $15 for the baseline assessment and $35 for the post-assessment one month after. Institutional review boards (IRB) at the University of Pennsylvania approved the study.

Setting and Participants

Participants were recruited in the Philadelphia area through advertising on social media including targeted ads on Facebook and Instagram, through flyers posted on streets near supermarkets, parks, shopping malls, and bars expecting a high African American women turnout, and through the referrals of participants (i.e., snowballing) from December 2015 to January 2016. Eligible participants were African American women (self-identified), aged 18 to 35, using an Android smart phone, and residing in Philadelphia. Individuals were excluded if they were already participating in another physical activity study, were not able or willing to carry an Android smart phone, were pregnant, or stated that they could not complete the study. Participants provided written
informed consent, completed an online sociodemographic questionnaire, and received objective assessment of their height, weight, and a 1-minute push-up test at a research office during their initial screening visit.

Intervention and Randomization

The PennFit mobile app intervention was developed based on formative research with the target population and theories that emphasize the role of descriptive social norms in predicting behavior change. Descriptive norm describes what is typical or normal. The integrative model of behavioral prediction (IMBP) postulates that perceived descriptive norm regarding whether one’s referent groups engage in the behavior directly influences one’s behavior intention. The focus theory of normative conduct (Cialdini et al., 1991; Cialdini et al., 1990) further asserts that norms are only likely to influence behavior directly when they are focal in attention thus salient in consciousness. The long-term efficacy of normative persuasive communications thus largely depends on continuously accessible normative information over time. To leverage this theoretical prediction, the PennFit mobile app allowed participants to continuously access other participants’ physical activity information and to develop supportive relationships through online conversations. For instance, seeing other participants’ updates on physical activity several times a day through 30 days would potentially build a stable normative perception that other people similar to me engage in physical activity regularly.

Formative research with a separate sample of 30 young African American women recruited from Philadelphia was conducted to elicit attitudes and opinions to develop the PennFit mobile app. One-on-one 30-minute interviews were conducted in September
2015. Among the 30 women, 20 were overweight to obese and no one used any fitness tracking device before. Although 7 women mentioned they had tried using or were currently using free health and fitness apps, they did not use the apps consistently on a daily or weekly basis. Most of them used apps for losing weight and did not find them effective. Only 2 of them used fitness apps that demonstrated how to do muscle-strengthening activities. In addition, no one used any app that incorporated social networking functions either to connect with strangers or their families or friends. These women identified two common reasons for not using the apps consistently. One is that they simply forgot to use the apps and the other is that they did not find them effective as expected. When asked about what makes it easy for them to engage in regular physical activity, the majority of the women mentioned having more time, having daily reminders, and having some form of social support would be helpful. Specifically, they mentioned they did not have close friends who exercised regularly and they liked the idea of having new exercise buddies.

Based on the formative research findings, we designed the PennFit app to provide daily reminders and to provide online connections that allow women to see other women’s daily exercise efforts and to exchange information through an online chatting tool. In addition, to enhance engagement, we allowed women to manually enter their daily exercise minutes and specific workouts. After the formative research and the app development, a 1-month pilot testing with 5 of these formative research participants was conducted to ensure usability before recruitment.

Eligible participants first attended a 2-hour introductory session by trained facilitators using standardized intervention manuals. The facilitators first briefly
discussed the health benefits of physical activity and the national guidelines for both aerobic and muscle-strengthening activity. Specifically, participants were encouraged to achieve 10,000 steps per day and to engage in a combination of aerobic and strength-building exercises each week: (1) at least 30 minutes of moderate-intensity aerobic physical activity on 5 days or at least 20 minutes of vigorous-intensity aerobic physical activity on 4 days and (2) strength-building activity on at least 2 days (Department of Health and Human Services, 2008). Facilitators then taught exercise movements and techniques covering both cardio and muscle exercises that participants could easily do at home without using any exercise equipment. Participants went through all exercise movements with the facilitator together for about 30 minutes.

Participants were electronically randomly assigned to the online network condition or to the individual control condition. Participants assigned to the online network condition were then electronically randomly assigned to 4-person networks. All participants first created their app profiles, including a username, profile picture, age, and favorite exercise. Each participant’s BMI was automatically added into the profile based on the measured height and weight at baseline. All participants were given a Fitbit (zip) to track their daily exercises. Fitbit (zip) is a small wireless wearable fitness tracking device that track active minutes, steps, and active calories burned. It fits comfortably in a pocket or on a belt and can be worn all day long (see Figure 6.1).

Figure 6.1. Fitbit (zip) clipped in a pocket.
All participants used the PennFit app to track their daily steps and the minutes for vigorous, moderate, and muscle-strengthening exercises that they completed for each day. All participants also received system-generated notifications that reminded them to wear their Fitbit in the morning and to log their activity minutes in the evening.

Participants in the control condition could see only their own profiles and physical activity logs. Participants in the online network condition could see both their own information and the profiles and activity logs of the three other women assigned to their network. In addition, they could send messages to the network through an instant chatting tool. Participants in the network condition were not given special instructions to compare with or support their network members. The interfaces of the PennFit app for the individual control condition and the online network condition are shown in Figure 6.2.

On the screen of the individual control condition, participants could see their own profile picture, username, weight, height, age, BMI, and favorite exercise. They could also update these information by clicking on the “change” button. The score bars on the screen show participants’ activity levels by each day. By clicking on the score bar, they could see the breakdown of different exercises including steps, moderate, vigorous and muscle activities. The steps were objectively recorded from the Fitbit and participants updated their estimated minutes for moderate, vigorous and muscle activities manually. The manually updated information was only used for participants to track their exercise efforts and not used for data analyses. On the screen of the online network condition, each participant could see the other three participants’ profile information and their activity levels by each day. For instance, the pink bar showed one participant had 6005
steps, 1 minute for doing squats, sit-ups, and push-ups, 1 minute for dancing, and 5 minutes for walking and climbing steps for a particular day.

Figure 6.2. Example interfaces of the PennFit app for the individual control condition (left) and the online social network condition (right). The profile pictures were obscured in this figure to protect participants’ privacy. The actual pictures were not obscured in the PennFit app.

**Measurements**

**Behavior Outcomes**

All active exercise minutes, steps, and active calories burned were collected from Fitbit’s application program interface. The primary outcome was the active exercise minutes objectively recorded by Fitbit every day throughout the program. Fitbit has been shown to be a valid device to measure physical activity (Ferguson, Rowlands, Olds, & Maher, 2015; Vooijs et al., 2014). Fitbit records active minutes when the activity is more
strenuous than regular walking. Active minutes are calculated using metabolic equivalents (METs), covering light (1.79 – 3.99 METs), moderate (4 – 5.99 METs) and vigorous (>= 6 METs) activities. A Met of 1 indicates a body at rest. Fitbit estimates MET value in any given minute by calculating the intensity of the activity. Active minutes are recorded for activities at or above 3 METs. We hypothesized that participants in the online network condition would have a significantly greater number of active minutes per day than the control group during the 30-day intervention. The secondary outcomes included the number of steps per day and the number of active calories per day. We hypothesized that participants in the online network condition would have a significantly greater number of steps per day and greater number of active calories per day, than the control group. In addition, participants’ height, weight, and the number of pushups they could do within 1 minutes were measured at both baseline and post-intervention assessments.

Other than the objective measures, participants also reported their days for physical activity in the past 7 days with 3 items the Centers for Disease Control and Prevention developed (Centers for Disease Control and Prevention, 2001). The outcome was a weighted average of the number of days on which participants reported engaging in 20 minutes of vigorous-intensity activity, 30 minutes of moderate-intensity activity, and strength-building activity, in the past 7 days. The 2008 physical activity guideline (Department of Health and Human Services, 2008) requires 20 minutes of vigorous-intensity activity on at least 4 days or 30 minutes of moderate-intensity activity on at least 5 days and engaging in strength-building activity on 2 or more days, in the past 7 days. Accordingly, the weighted average was calculated by assigning different weights for the
3 behaviors (Jemmott et al., 2015b). Specifically, the weighted average was calculated as follows:

\[
\frac{\text{days of vigorous activity} + \text{days of moderate activity}}{2} \times 5 + \text{days of strength building activity} \times 2) / 7
\]

**Theoretical Variables**

Theoretical variables were measured in the baseline and the post-assessment online surveys. Although the PennFit mobile app was designed primarily to influence descriptive social norms, other relevant IMBP psychological variables could also be influenced by continuous behavior modifications through the intervention. Six theoretical variables were addressed in the intervention regarding physical activity.

Attitude towards physical activity was assessed by averaging 4 items concerning behavioral beliefs on physical activity (\(\alpha = 0.76\)) (Jemmott, 2014, 2015a, 2015b). Participants rated on a 5-point scale indicating how bad/good, foolish/wise, dangerous/safe, and harmful/beneficial it is to exercise for 30 minutes at least 5 times a week in the next month.

Subjective norm towards physical activity was assessed by averaging 3 items (\(\alpha = 0.79\)) (Jemmott, 2014, 2015a, 2015b). Participants rated on a 5-point scale (1 for “Strongly disagree” to 5 for “Strongly agree”), indicating whether they believed most people who are important to them would approve or disapprove physical activity. An example item is “Most people who are important to me would think it is okay for me to exercise for 30 minutes at least 5 times a week in the next month.”
Descriptive norm towards physical activity was assessed by averaging 2 items (α = 0.83) (Jemmott, 2014, 2015a, 2015b). The question asked “How many of your 5 closest friends exercise for 2 hours and 30 minutes (150 minutes) of moderate aerobic activity (i.e., brisk walking) OR 1 hour and 15 minutes (75 minutes) of vigorous aerobic activity (i.e., jogging or running) every week?” The second question asked “How many of your 5 closest friends do muscle strengthening exercises such as push-ups, sit-ups, or weight lifting at least 2 days a week?” Responses ranged from 0 to 5.

Self-efficacy towards physical activity was assessed by averaging 2 items (α = 0.92) (Jemmott, 2014, 2015a, 2015b). Participants rated on a 5-point scale (1 for “Strongly disagree” to 5 for “Strongly agree”) for statements “I am confident that I can overcome obstacles that might prevent me from exercising for 30 minutes at least 5 times a week in the next month” and “I am sure that I can exercise for 30 minutes at least 5 times a week in the next month.”

Intention for physical activity was assessed by averaging 3 items (α = 0.87) (Jemmott, 2014, 2015a, 2015b). Participants rated on a 5-point scale (1 for “Strongly disagree” to 5 for “Strongly agree”) indicating whether they intended to exercise in the future. An example item is “I plan to exercise for 30 minutes at least 5 times a week in the next month.”

In addition, social support regarding physical activity was assessed by averaging 12 items (α = 0.85) of the Friend Support for Exercise Habit Scale (Sallis, Grossman, Pinski, Patterson, & Nader, 1987). Participants rated on a list of things friends or acquaintances have said or done to them during the past month. Example items included
“Exercised with me,” “Gave me encouragement to stick with my exercise program,”
“Planned for exercise on recreational outings.”

Statistical Analysis

A priori, we assumed a 1-tailed test based on a firm directional hypothesis. With \( \alpha = 0.05 \), 15% attrition, an effect size of Cohen’s \( d = 0.50 \) standard deviations, intraclass correlation coefficient (ICC) = 0.02, and the average correlation among reports of physical activity over repeated assessments, \( r = 0.24 \) (El-Bassel et al., 2011), a total of 80 women would yield statistical power of 80%. We used descriptive statistics to summarize the sociodemographic characteristics at baseline and chi-square test and logistic regression to analyze attrition.

Main Effects on Logins, Active Minutes, Steps, and Calories

For each participant on each day of the study, we obtained the number of PennFit app logins, active minutes, steps, and active calories as continuous variables. Behavior data could be missing for any day if a participant did not wear the Fitbit. For these analyses, we used all available data. We tested the online network intervention’s efficacy compared with the control condition using linear generalized-estimating-equations (GEE) models (Fitzmaurice, Laird, & Ware, 2004; Liang & Zeger, 1986), adjusting for longitudinal repeated measurements and participants clustered within networks. The model on PennFit app login included intervention condition and time (30 categories representing 1 to 30 days). The models on active minutes, steps, and calories included intervention condition and time (29 categories representing 2 to 30 days). Because participants started to wear the Fitbit at the evening of the first day, behavior data from
the first day were not used. We report estimated mean differences for continuous outcomes and their corresponding 95% confidence intervals. We used robust standard errors and specified an independent working correlation matrix. In addition, we report the results of all models adjusting the baseline measure of participants’ self-reported physical activity.

**Mediation Effects**

To analyze the intervention’s effects through psychological mediating variables. We performed a serial multiple-mediation analysis on all potential mediators simultaneously implemented with Mplus Version 7 for Windows (Muthén & Muthén, 2012). All theoretical mediators (i.e., attitude, subjective norm, descriptive norm, self-efficacy, social support, and intention) and the outcome were measured at immediate-post intervention. Because changes on objective exercise behaviors already happened before the post-assessment, we could only use the self-reported physical activity as an outcome in this mediation analysis. This method uses maximum likelihood estimates (ML) (Little & Rubin, 2002; Muthén & Muthén, 2012). The model, based on the IMBP (Fishbein & Ajzen, 2010), has paths from the intervention to attitude, subjective norm, descriptive norm, and self-efficacy, a path from each of them to intention, a path from intention to the physical activity. In addition, the model has a path from the intervention to social support, and a direct path from social support to physical activity. Attitude, subjective norm, descriptive norm, self-efficacy, and social support were allowed to correlate with each other. All the dependent variables in the SEM model were continuous variables; accordingly, Mplus estimated all path coefficients via linear regression. The regression
models predicting intention and physical activity adjusted for the intervention, and the
model predicting each theoretical variable adjusted for the corresponding baseline of the
variable. All regression models adjusted for baseline physical activity. Mplus calculated
the indirect effect through each theoretical path using the product-of-coefficients
approach (MacKinnon et al., 2002; MacKinnon, Lockwood, & Williams, 2004). We used
the bootstrap method (bootstrap=5000) with maximum likelihood estimators (Olsson,
Foss, Troye, & Howell, 2000). Significant mediation was determined by testing whether
the product’s corresponding bias-corrected bootstrap ACI contained zero.

**Results**

Figure 6.3 reports trial enrollment and participation. All randomly assigned
participants (n=91) returned for post assessment and were included in the analyses.

![Flow diagram of participants through the trial.](image)
Table 6.1 reports participants’ baseline sociodemographic characteristics. Participants had a mean age of 26.8 years (SD = 5.1). In total, 14.3% were married, 29.7% had children, and 33% had monthly income less than $850. The mean BMI was 31.6 (SD = 0.8), over half (52.8%) were obese and 25.3% were overweight. Only 33% met the 2008 physical activity guideline. On average, participants rated their overall quality of life as good. Participant characteristics were not significantly different between the two conditions, except that more participants in the control condition had monthly income less than $850 (Chi 2 [2] = 11.23, p = 0.004).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Total (n = 91)</th>
<th>Control (n = 47)</th>
<th>Online Network (n = 44)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean age (SD), y</td>
<td>26.8 (5.1)</td>
<td>26.4 (5.4)</td>
<td>27.2 (4.7)</td>
</tr>
<tr>
<td>Married, n (%)</td>
<td>13 (14.3)</td>
<td>5 (10.6)</td>
<td>8 (18.2)</td>
</tr>
<tr>
<td>Children, n (%)</td>
<td>27 (29.7)</td>
<td>15 (31.9)</td>
<td>12 (27.3)</td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school diploma</td>
<td>8 (8.8)</td>
<td>6 (12.8)</td>
<td>2 (4.6)</td>
</tr>
<tr>
<td>2-year college</td>
<td>34 (37.4)</td>
<td>20 (42.6)</td>
<td>14 (31.8)</td>
</tr>
<tr>
<td>4-year college</td>
<td>29 (31.9)</td>
<td>12 (25.5)</td>
<td>17 (38.6)</td>
</tr>
<tr>
<td>Post-graduate</td>
<td>20 (22.0)</td>
<td>9 (19.2)</td>
<td>11 (25.0)</td>
</tr>
<tr>
<td>Employed, n (%)</td>
<td>79 (86.8)</td>
<td>39 (83.0)</td>
<td>40 (90.9)</td>
</tr>
<tr>
<td>Monthly income, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than $850</td>
<td>30 (33.0)</td>
<td>23 (48.9)</td>
<td>7 (15.9)</td>
</tr>
<tr>
<td>$851 to $2500</td>
<td>35 (38.5)</td>
<td>14 (29.8)</td>
<td>21 (47.7)</td>
</tr>
<tr>
<td>$2501 or more</td>
<td>26 (28.6)</td>
<td>10 (21.3)</td>
<td>16 (36.4)</td>
</tr>
<tr>
<td>Mean overall quality of life (SD) a</td>
<td>3.3 (0.8)</td>
<td>3.4 (0.7)</td>
<td>3.3 (0.9)</td>
</tr>
<tr>
<td>Mean BMI (SD), kg/m^2</td>
<td>31.6 (8.2)</td>
<td>30.4 (6.8)</td>
<td>33.0 (9.4)</td>
</tr>
<tr>
<td>Overweight, n (%)</td>
<td>23 (25.3)</td>
<td>15 (31.9)</td>
<td>8 (18.2)</td>
</tr>
<tr>
<td>Obese, n (%)</td>
<td>48 (52.8)</td>
<td>22 (46.8)</td>
<td>26 (59.1)</td>
</tr>
<tr>
<td>Met physical activity guideline, n (%) b</td>
<td>30 (33.0)</td>
<td>15 (31.9)</td>
<td>15 (34.1)</td>
</tr>
<tr>
<td>Mean days for vigorous activity (SD)</td>
<td>2.6 (1.7)</td>
<td>2.7 (1.5)</td>
<td>2.6 (1.8)</td>
</tr>
<tr>
<td>Mean days for moderate activity (SD)</td>
<td>4.0 (2.3)</td>
<td>4.1 (2.3)</td>
<td>3.9 (2.2)</td>
</tr>
<tr>
<td>Mean days for muscle-strengthening activity (SD)</td>
<td>2.4 (1.7)</td>
<td>2.3 (1.6)</td>
<td>2.5 (1.9)</td>
</tr>
</tbody>
</table>

Note. a Overall quality of life was rated on a 5-point scale: 1 (Poor), 2 (Fair), 3 (Good), 4 (Very good), 5 (Excellent).

b The 2008 physical activity guideline requires 20 minutes of vigorous-intensity activity on at least 4 days or 30 minutes of moderate-intensity activity on at least 5 days and engaging in strength-building activity on 2 or more days, in the past 7 days.
Effects on Engagement

The total percentage of participant-days on which step-count data were missing during the 30-day intervention was 7.1%. The network condition had fewer missing days (4.9%) than did the control condition (9.2%) (Chi 2 [1] = 19.74, p < 0.001). As time went on, the missing days increased in general (OR = 1.05, p < 0.001) and increased faster in the control condition (p = 0.001). The total percentage of participant-days for 30 days on which login data of the PennFit app were missing during the intervention was 44.0%. The network condition had less missing days (38.4%) than the control condition (49.3%) (Chi 2 [1] = 32.76, p < 0.001). As time went on, the missing login days increased in general (OR = 1.16, p < 0.001) and increased faster in the control condition (p = 0.018).

More specifically, the mean number of logins per day was 6.93 (SD = 6.56) in the network condition and 5.54 (SD = 5.24) in the control condition. Figure 6.4 shows the mean login numbers by day and by experiment condition.

![Figure 6.4. Mean login numbers by day and by experiment condition.](chart)

The network condition increased the number of logins by 1.58 (95% CI: 0.31, 2.84) in comparison with the control condition (p = 0.015). As time went on, the number
of logins decreased by 0.18 (95% CI: -0.24, -0.12) per day (p < 0.0001). In addition, the Intervention x Time interaction was significant (p = 0.032). These indicate that although uses of tracking devices and apps decreased over the 30 days, participants in the network condition adhered to their Fitbit and adhered to using the PennFit app more consistently than those in the control condition throughout the intervention.

**Effects on Active Minutes, Steps, and Calories**

Table 6.2 summarizes the mean active minutes, steps, and active calories per day by intervention condition over 29 days. On average, participants had 175.5 (SD = 82.2) active exercise minutes, 7400.3 (SD = 4359.8) steps, and 759.3 (SD = 404.1) active calories per day during the intervention.


<table>
<thead>
<tr>
<th>Variable</th>
<th>Total</th>
<th>Control</th>
<th>Online Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD) active exercise minutes</td>
<td>175.5 (82.2)</td>
<td>175.6 (84.3)</td>
<td>175.3 (80.0)</td>
</tr>
<tr>
<td>Mean (SD) steps</td>
<td>7400.3 (4359.8)</td>
<td>7512.7 (4243.2)</td>
<td>7285.6 (4474.5)</td>
</tr>
<tr>
<td>Mean (SD) active calories</td>
<td>759.3 (404.1)</td>
<td>754.5 (394.2)</td>
<td>764.2 (414.1)</td>
</tr>
</tbody>
</table>

Figure 6.5 shows the mean active exercise minutes by day and by experiment condition. Steps and active calories followed the same patterns.
Table 6.3 presents estimated intervention effects on the three behavior outcomes unadjusted and adjusted for baseline outcome. The online network intervention did not impact the three behavior outcomes compared with the control condition in any analysis. In the adjusted analyses, self-reported physical activity at baseline predicted active minutes (mean difference = 9.03, 95% CI: 2.30, 15.76, p = 0.009), steps (mean difference = 740.08, 95% CI: 418.91, 1061.26, p <.0001), and active calories (mean difference = 58.45, 95% CI: 23.54, 93.37, p = 0.001) over the 29 day period.
Table 6.3. GEE significance tests for the intervention effects on physical activity and active calories unadjusted and adjusted for baseline activity, African American women, Philadelphia, PA, 2016.

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Unadjusted for Baseline</th>
<th>Adjusted for Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (95% CI)</td>
<td>P value</td>
</tr>
<tr>
<td>Active exercise minutes</td>
<td>-0.33 (-19.60, 18.94)</td>
<td>0.973</td>
</tr>
<tr>
<td>Steps</td>
<td>-226.18 (-1276.14, 823.79)</td>
<td>0.673</td>
</tr>
<tr>
<td>Active calories</td>
<td>9.55 (-90.68, 109.78)</td>
<td>0.852</td>
</tr>
</tbody>
</table>

Note. Estimate is mean difference and CI is confidence interval.

Effects on Self-reported Physical Activity and Mediators

The mean weighted average days for self-reported physical activity was 3.05 (SD = 1.38) at baseline assessment and 4.05 (SD = 1.24) at the post assessment. For all participants, the self-reported physical activity significantly increased after the intervention (p < 0.0001). The online network intervention did not have significant impact on this self-reported physical activity in comparison with the control condition. Table 6.4 summarizes the means and standard deviations of self-reported physical activity and theoretical variables assessed at baseline and post-intervention by condition. These descriptive data clearly showed that participants’ perceived peer norm and social support were much lower than other theoretical variables. These African American women saw their friends as not engaging in physical activity and received very little social support for engaging in physical activity.
Table 6.4. Self-reported physical activity and theoretical variables assessed at baseline and post-intervention of participating African American women by intervention condition, Philadelphia, PA, 2016.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Control</th>
<th>Online Network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Post</td>
</tr>
<tr>
<td>Self-reported physical activity</td>
<td>3.06 (1.35)</td>
<td>4.05 (1.32)</td>
</tr>
<tr>
<td>Attitude</td>
<td>4.44 (0.50)</td>
<td>4.69 (0.44)</td>
</tr>
<tr>
<td>Injunctive norm</td>
<td>4.28 (0.73)</td>
<td>4.51 (0.59)</td>
</tr>
<tr>
<td>Peer norm</td>
<td>2.14 (0.90)</td>
<td>2.18 (0.84)</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>4.04 (0.81)</td>
<td>4.13 (0.75)</td>
</tr>
<tr>
<td>Social support</td>
<td>2.51 (0.60)</td>
<td>2.67 (0.54)</td>
</tr>
<tr>
<td>Intention</td>
<td>4.31 (0.56)</td>
<td>4.48 (0.56)</td>
</tr>
</tbody>
</table>

Figure 6.6 shows the mediation model with unstandardized coefficients and bootstrapped 95% confidence intervals. The online network condition did not have significant impact on the hypothesized mediators. Consistent with the IMBP, intention was related to self-reported physical activity and related to attitude, subjective norm, and self-efficacy. However, peer norm was not related to intention and social support was not related to physical activity.
Figure 6.6. Structural equation model of the effects of the online network intervention on theoretical variables and weighted average physical activity.

**Online Messages**

During the 30-day intervention, participants in the online network condition generated 329 short messages in total. All 44 network-condition participants sent messages to their groups. The number of messages per person ranged from 1 to 23 (mean = 7.5, SD = 4.9). The least active group generated 15 messages whereas the most active generated 77 messages. All messages were positive and mostly about emotional and informational support, such as sending encouragement and sharing specific exercise suggestions. Table 6.5 shows two examples of the short conversations.
Table 6.5. Example online conversations in the network condition.

Conversation 1:

Hey ladies!! Hope everyone is good day. It's nice out, so I'm definitely taking advantage of the good weather after work!!

Yes get out there and get moving. You can do it :-)

Ugh, have about 2,000 steps to hit the goal for today. Guess I'll make a target run lol

Get that 2000! If u do a line dance like the wobble or cupid shuffle 2/3 times u will have ur steps with no prob.

Oh thanks, I'll do that too lol

Conversation 2:

Ms She and Mika: how do you both get so many steps/points yesterday? !??!?!!

This study making me realize how sedentary I am

I had no choice... I was running errands for my boss ... Today was a slow day so im about to jump on the treadmill for a bit

My step goal is 15000 on my cardio days. I do at least about 2.5/ 3 miles 5 times a wk.

I also walk .50 mile to train before work and then the same distance back after.

I def need to change my lifestyle =) my points include me marching in place at my desk during the day & running stairs at home

I usually carry my phone in my hand everywhere I go cause it counts steps, now I have this and I can leave it down some

Reesie, I am right there with you!! I purposely climbed 7 flights of stairs 2x to try and get my numbers up!!!

Right i usually use my phone but i would lose steps when it was on the charger or dead

I just got out of my bossy bunz class. Still have 3000 steps to go. Not gon happen. Scandal is on...
Discussion

This mobile app based online network intervention aimed to leverage theoretical predictions of the normative influence and the IMBP. The PennFit mobile app was developed based on formative research with African American women and allowed participants in the online network condition to continuously access other participants’ physical activity information and to develop supportive relationships through online conversations. During the 30 days, all participants significantly increased their self-reported physical activity. The average number of 7400.3 steps per day among these inactive women is encouraging. Although we did not obtain their average steps before the study, other studies have reported that U.S. adults took an average of 5117 to 6564 steps per day (Bassett, Wyatt, Thompson, Peters, & Hill, 2010; Tudor-Locke, Brashear, Johnson, & Katzmarzyk, 2010). Exposures to Fitbit and the PennFit app alone may have significantly increased these women’s steps and exercise activities. Because the study did not have eligibility criteria based on physical activity levels, our voluntary sample might have high activity levels to begin with in comparison with the average.

Furthermore, the intervention condition significantly increased participants’ uses of the Fitbit device and the PennFit app, indicating that mobile-based online network interventions with strangers were feasible and welcomed among young African American women. Encouraging these inactive women to use Fitbit and the PennFit app is a significant achievement. Consistent self-monitoring has been shown an effective strategy in increasing exercises (Carels et al., 2005; Gleeson-Kreig, 2006). A lot of mobile apps incorporated self-monitoring (Conroy, Yang, & Maher, 2014), however, it is not clear
how long people could adhere to using these apps. Building in online networks could increase adherence and potentially generate effects on behavior change in the long term.

However, the intervention did not generate substantial impact on objectively recorded physical activity outcomes or theoretical variables in comparison with the control condition. Especially, after 30 days of engaging with the PennFit app, participants still perceived that other African American women were not engaging in physical activity and perceived receiving little social support. Participants in the online networks generated 329 messages throughout the intervention, which translates into about one message per network per day. The conversations were all positive and encouraging and we found no negative or demoralizing comments that discourage participants from engaging in exercises. However, the low frequencies of supporting conversations seem to be inadequate to generate changes in perceived norms and social support.

There were several possible explanations for the null findings on physical activity. First, participants in the network condition engaged more with the PennFit app and exchanged emotional and informational support with each other. However, these behaviors did not lead to significant gains in steps or exercises among the network members. Because we found no impact of the intervention on any of the mediators, it was difficult to know which part of the intervention was working or not working. Substantial changes in daily physical activity indeed require a lot of effort over time. As illustrated in one of the example conversations, some individuals’ daily routines provide less opportunities for exercises whereas others’ require walking to different places. It is possible that merely seeing and comparing with other people’s behavioral efforts were not effective in increasing these women’s activity levels. Other than that, it is also
possible that the frequencies of emotional and informational support exchanges were not high enough in these stranger online networks. Participants occasionally got motivated but could not effectively incorporate that into their daily routines. The current findings are similar to several other studies comparing online network conditions that have found changes over time but not between groups over time (Cavallo et al., 2012a; McKay, King, Eakin, Seeley, & Glasgow, 2001).

Second, participants in both conditions received a 2-hour introductory session teaching them the national guideline of physical activity, the health benefits of recommended levels of physical activity, and specific instructions on how to exercise with minimum equipment. This introductory session seemed to be effective in boosting all participants’ intention to exercise. The session did not have special instructions for the network members to stimulate normative comparisons or supportive relationships. Different from past studies that utilized additional incentives for social comparison or support (Zhang, Brackbill, Yang, & Centola, 2015), this study assumed that participants’ engagement with the online networks over time would bring sufficient changes. This assumption seemed to be too strong. After the introductory session, all individuals’ steps and exercise minutes stayed relatively at the same level throughout the intervention. Future research should consider adding in additional incentives to stimulate social interactions to start at the beginning and to boost interactions throughout the intervention.

Third, participants in both conditions received the Fitbit and installed the Fitbit app on their phone. Although all of them were instructed to not use the Fitbit app, the app automatically sent notifications and encouraging messages based on individuals’ step achievement. Although participants in the control condition did not have access to other
participants in the study, they still received a fairly strong treatment from Fitbit itself. Monitoring one’s own steps and activity levels on Fitbit seemed to contribute a lot to these participants’ behavior change effort. The formative research suggested very few women in our sample ever used Fitbit or other fitness trackers before. The Fitbit treatment might brought some novelty effect that kept individual participants exercising in the control condition. We did not have data on participants’ baseline exercises including active minutes and steps, so we did not know how much the control condition increased participants’ activity levels. Future research should have participants wear the device for a week prior to randomization to get a baseline measure of the activity levels. Also, future research should use less active control conditions in order to understand the basic effects of online networks.

Finally, the study is limited by its small sample size and the intervention length. The survey data were only collected on 91 individuals, thus the mediation analyses might not have enough power to detect significant differences. All theoretical variable measures were validated in previous studies (Jemmott et al., 2014, 2015a, 2015b) and show good reliability in the current sample. If we had a bigger sample we might be able to detect changes on dimensions of perceived peer norms and perceived social support. The intervention length was short in comparison with Study 1 (13 weeks) and Study 2 (11 weeks). Study 1 showed that the effects of the online networks got stronger in the second half of the program (week 7 to week 13) in comparison with the media and the control conditions. It is possible that if we followed these participants for two more months, we would find significant increases in exercises in the online network condition in comparison with the control condition.
To our knowledge, this is the first study to test a mobile app based online network intervention among young African American women. It demonstrated the feasibility of this approach and found that all participants significantly increased their self-reported physical activity after the study. The online network intervention significantly increased participants’ engagement with the fitness tracker and the mobile app. Although it did not show significant effects on objectively measured behaviors or psychological outcomes, the descriptive data are still useful in understanding this population’s behaviors under the influence of persuasive technologies. Future research need to address the above discussed limitations and test this approach with a larger sample and longer follow up assessments.
CHAPTER 7

DISCUSSION AND CONCLUSION

Summary and Discussion

Young adults are increasingly using online resources to improve their health. Data from 2014 showed 64% of American adults owned a smart phone and 62% of the smartphone owners used their phone in the past year to look up information about a health condition (Smith & Page, 2015). Approximately 78% of mobile health app users use fitness apps ("Mobile Analytics Report," 2015). However it is not clear how long people would keep using these apps. Our formative research with young African American women suggested very few women in our sample ever used Fitbit or other fitness trackers before. This trend and potential disparity will invariably trigger more research concerning effective designs of online physical activity interventions employing websites and mobile apps for individuals with diverse backgrounds. Despite the popularity of commercial fitness apps that incorporate social media support including Facebook and Twitter, their efficacy for increasing physical activity is largely unknown (Conroy et al., 2014), in part because they oftentimes bundle up multiple behavior change techniques that present a challenge for researchers to conduct rigorous evaluations. These apps have not been evaluated in randomized controlled trials.

This dissertation research makes an important contribution to understanding how to design effective online network-based physical activity intervention. It offers a thorough discussion of three relevant theoretical frameworks to clarify the effects of online networks on behavior change. It provides empirical evidence on the efficacy and
mechanisms of online network interventions in improving physical activity through psychological pathways. The key findings can be summarized as follows.

First, online social network interventions can increase young adults’ physical activity compared with the individual control condition. Study 1 showed in comparison with the control condition, online networks significantly increased overall exercise class enrollment ($p = 0.02$), producing a 167% increase in the fraction of participants above the 75th percentile of enrollment compared with the control condition. This indicates that the online networks motivated some active participants to be more active throughout the 13-week study. The online networks significantly increased enrolling in at least 6 classes in comparison with the individual control condition ($p < 0.0001$). Study 2 showed in comparison with the control condition, online networks eliciting social comparison increased participants’ probability of attending exercise class. In comparison with the individual control condition, the social comparison condition increased attendance rates by 99% ($p = 0.01$) and the combined (team comparison) condition increased attendance rates by 33% ($p = 0.078$), approaching statistical significance. In contrast, the social support condition did not impact attendance ($p = 0.869$). These results suggest emphasizing social comparison with other participants in online networks is an effective strategy in increasing physical activity levels. Furthermore, Study 3 showed in comparison with the control condition, online networks significantly improved participants’ adherence to using the Fitbit tracker and increased their daily logins of the PennFit app by 1.58 times ($p = 0.015$). It is important to note that all online networks implemented in these studies shared the following characteristics: small networks with sizes ranging from 4 to 6; networks with strangers who share similar sociodemographic
characteristics; networks focusing individuals’ attention to their peers’ positive behavior change signals. The consistent results suggest that these network design features can make online network interventions effective in changing physical activity related behaviors.

Second, although online networks were equally capable of communicating behavior signals to network peers, different framings and designs of the network interface would induce different levels of social influence. In Study 2, exposing individuals to relevant reference points for comparison, whether those reference points were other individuals or other teams, increased responsiveness to the physical activity of their network peers. In contrast, focusing individuals on an aggregate team performance might suppress the social influence dynamics. Effective online social networks generated behavior clustering within the artificially created networks although participants were all strangers before they were put into the networks. For instance, exercise class attendance rates were similar among network peers in the two effective network conditions involving social comparison. The intraclass correlation was 0.12 (95% CI: 0.04, 0.22) for the social comparison networks, and was 0.21 (95% CI: 0.09, 0.38) for the team comparison networks. In contrast, the intraclass correlation was 0.07 (95% CI: -0.02, 0.21) and not significant for the social support networks. These results suggest that the social influence dynamics can be stimulated through social comparison among strangers. Although social support has often been identified in online health groups, the supportive messages may emphasize more on acknowledging individual differences and enhancing self-esteem (Fukkink, 2011; Mo & Coulson, 2008) than stimulating interpersonal influences.
Third, the studies aimed to explore theoretical mediators. Based on a sample of only 91 individuals, Study 3 provided descriptive statistics on theoretical mediators assessed at post-intervention. The data show that young African American women held high levels of positive attitudes, injunctive norms, self-efficacy, and intention for physical activity. However, they did not perceive a strong peer norm or social support on physical activity. These two areas need to be targeted with stronger interventions. Study 3 can be enhanced by providing more instructions and incentives on building social relationships.

Fourth, analyses on cumulative exercise class enrollments in Study 1 suggest that the effects of online social networks become stronger in the second half of the intervention program. The significant difference between the social condition and the media condition emerged after week 6. While the effects of media messages and online networks were comparable at the beginning of the program, online networks were significantly more effective at increasing enrollments towards the end of the program. In Study 2, the effects of the two social comparison conditions remained strong throughout the program. Study 3 only tracked participants’ exercise activities during one month, it is possible that significant effects of online networks in comparison with the individual control would emerge if the program had a longer intervention time.

**Strengths and Limitations**

This dissertation research is strengthened by several design features. The method of constructing online networks and randomization solved the problem of causal identification in previous correlational studies or quasi-experiments that intervened on people’s existing social networks. When people join a study with their families or friends,
their baseline behavior patterns are already similar (i.e., high baseline level of homophily, McPherson et al., 2001). For instance, friends who join a study as a group together may already share similar physical activity levels. As they together increase physical activity levels, it becomes more difficult to detect if correlations of individuals’ behaviors become larger after intervention. When people join a study and get randomly assigned into online networks, it is assumed that individuals in a network do not share similar behavior patterns. The significant correlations of individuals’ behaviors in effective online networks after intervention indicate that artificially constructed online networks can facilitate social influence dynamics that make people more similar to each other in a network regarding exercise behaviors.

In addition, unlike previous interventions using self-reported behaviors that may be subjected to recall bias, this research explored using objectively and longitudinally collected behavior measures as outcomes. Particularly, Study 3 incorporated a wearable device (Fitbit zip) to track active exercise minutes and steps and continuously fed the data into the mobile app intervention, which enabled automated continuous updates on network peers’ behavior change. Participants wore their Fitbit from morning till night so all data were collected in natural settings. Past research that utilized smartphones to collect step numbers may not capture the full range of daily activity. More importantly, compared to active minutes, phone-based assessments of steps cannot capture the effort spent on moderate and vigorous physical activities (Aharony, Pan, Ip, Khayal, & Pentland, 2011). Although Study 3 did not find a difference between conditions on the objective measures, it provided valuable information for understanding young African American women’s behavior patterns over 30 days.
Finally, this research explored theoretical mechanisms of online network effects on physical activity behaviors. Study 2 experimented with two different social mechanisms, social support and social comparison. The social comparison factor showed to be effective in motivating individuals to attend exercise classes. Study 3 measured IMBP theoretical variables after the intervention. Although self-reported physical activity was related to IMBP variables, the online network treatment did not impact the theoretical variables in comparison with the control condition. The low levels of perceived norms and social support suggest that future research on African American women need to focus on targeting these two areas. In addition, future research should consider using measures that are more sensitive to descriptive norm and social support of constructed online networks. The questions used in Study 3 concerned only participants’ friends and acquaintances’ exercise and supportive behaviors and did not specifically emphasize their online connections.

Notwithstanding the strengths, several limitations need to be acknowledged and to inform future research. The first limitation concerns the experiment design. Network interventions entail a variety of approaches. This dissertation research focused on a basic approach, constructing small online networks to enable social influence dynamics among strangers. The studies did not vary network topologies (i.e., size, density, homogeneity, centrality), thus did not examine different network topologies’ effects on psychological and behavior changes. Studies that examine the network effects require large sample sizes to systematically vary network structures or topologies (Centola, 2010). This dissertation takes a first step to establish the basic efficacy of constructed online networks on behavior change. Future research can go further to explore the frontier, theorizing and
examining the effects of different network-level characteristics. An additional similar limitation is that the dissertation studies involved only stranger networks and could not compare effects of different network compositions. Although the results show that stranger networks are effective in motivating people to engage with the physical activity program and fitness tracking devices, it is acknowledged that the majority of past network interventions targeted people’s existing networks involving families, friends, or colleagues (Foster et al., 2010; Leahey et al., 2012; Wing & Jeffery, 1999). Competing hypotheses can be tested in future research. It is possible that people’s existing networks can provide more social support whereas networks with strangers who share similar demographic and behavior traits are more effective in stimulating social comparison.

Second, the three studies in this dissertation did not collect behavior change data after the interventions. There were no follow-up assessments. Although behavior changes were significant during the time period when participants used the website and the mobile app, it is not clear whether participants could sustain their behavior change and incorporate regular physical activity after the intervention. Indeed, very few technology-assisted behavior change interventions had long-term follow-up assessments (Vandelanotte et al., 2016). The observed effects during the intervention may attenuate over time if people lose interest in the technology and decrease their engagement. A few studies showed that during the intervention, engagement with the technology decreased (Cavallo et al., 2012) and during the follow-up assessments, behavior change was not significantly different between the treatment and the control groups (Napolitano et al., 2013; Patel et al., 2016). In this research, the study websites for Study 1 and Study 2 were only used during the program to register for exercise classes. The fact that behavior
change did not decrease during the program suggest online networks helped sustain engagement. However, once the university program was completed at the end of the semester, the website was closed as well. Study 3 showed decreased engagement with the app during the intervention. Although the online networks helped to decelerate the decreasing rate, it is not clear whether participants would keep using the app or any other apps after the study. Future research is needed to examine people’s continued engagement with the technology platform and to show long-term effects of using online networks for physical activity promotion.

Third, generalizability is limited in this dissertation research. The first two studies involved only graduate students from one university. Compared with other populations, these students with advanced education may be more responsive to technology-based behavior intervention and to social comparison. The third study targeted young African American women who used Android smart phones in Philadelphia. These women have low levels of physical activity and are at higher risks for becoming obese and developing chronic diseases. During the study, these women requested more needs for technological assistance than did the graduate students in the other two studies. Whether these women could continuously engage with the mobile app and sustain behavior change remains unclear. Results of the three experiments cannot be overgeneralized to other populations. Future research can target adolescents, older populations, or patient populations to test the effects of online social network interventions.
Future Directions

This dissertation research experimented with different designs of using online networks for promoting physical activity among young adults. The studies’ limitations discussed above point to several promising future research directions, including the effects of network structure, the effects of network composition and formation, and the applications to other behavior change domains and populations.

Effects of Network Structure

Network structural characteristics, including size, density, homogeneity, centrality, can provide opportunities for psychological mechanisms. Currently, there is no thorough theoretical discussion on the links from different network structures to psychological mechanisms, and empirical tests are limited. Centola (2011) conducted two experiments manipulating online network structures and found that clustering and homophily in stranger online networks increased the rate of signing up for an online diet diary tool. When participants in the online social networks saw several other participants who were similar to them adopted the online tool, they were more likely to adopt the online tool themselves. These effects can be attributed to normative theories that argue people are influenced more easily by multiple behavior signals from similar others (Hogg & Reid, 2006).

This dissertation built on Centola’s findings and tested the effects of small homophilous stranger networks in promoting physical activity. Future research can work on the effects and mechanisms of network size and centrality. Past research on group conformity argues that the size of the group only affects conformity to an extent – as a
group expands past 4 to 5 people, the effect of conformity levels off or becomes negative depending on the specific conformity contexts (Bond, 2005). In online networks, keeping the local clustering levels similar and systematically varying networks sizes may generate different behavior change dynamics. In the context of health communication, when the number of network ties increases (e.g., increasing from 4 to 8), normative influence may become weaker given people’s attention to other peers’ behaviors can get diluted and less focused. This question deserves more theoretical and empirical tests.

On network centrality, recent work shows that in highly centralized information exchange networks where a small number of influential individuals have connections to most or all of the population, following the few influential individuals’ opinions can lead to a reduction in the accuracy of a group’s judgement. For instance, in a simple estimation task (e.g., estimating the caloric content of a meal), individuals first provided their estimations independently and then revised their estimations based on others’ estimations. Knowing others’ estimations in centralized networks significantly reduced the accuracy of the group’s average estimation in comparison with the baseline average of independent estimations. However, in decentralized networks where there is no influential individual and each individual has an equal number of connections to others, knowing others’ estimation improves both the accuracy of the group’s average estimation and the accuracy of individuals’ estimations (Brackbill, Becker, Herbert, & Centola, 2015). In other words, centralized networks can amplify a few individuals’ opinions in influencing other people’s judgment whereas decentralized networks allow everyone to exert equal influence to each other. These findings suggest decentralized networks can be applied in both community and individual health risk evaluations. Decentralized
networks may assist people in developing correct perceptions of their health risks (e.g., sexual infection risks, cancer risks, and chronic disease risks), which then impact their preventive health behaviors.

Effects of Network Composition and Formation

Network compositions or network tie characteristics, including strength, intimacy, and frequency of communication, can also provide opportunities for psychological mechanisms. Past physical activity interventions either examined stranger networks or networks composed of families, friends, or colleagues (Aharony et al., 2011; Foster et al., 2010; Leahey et al., 2012; Wing & Jeffery, 1999). The dissertation studies involved only stranger networks. Both types of network compositions can be effective in changing behaviors. It is possible that people’s existing networks with families and friends can provide more social support because of their greater emotional closeness whereas networks with strangers who share similar demographic and behavior traits are more effective in stimulating social comparison. On physical activity behaviors, Study 2 found that social comparison was a more effective motivator for increasing exercises through online networks. Future research can expand on it and test the effects of stranger versus familiar networks and their interactions with social support versus social comparison incentives. For instance, familiar networks may work better under social support incentives whereas stranger networks work better under social comparison incentives.

A related future direction is to provide opportunities for natural network formations. Different social environments can give rise to different network formations. For instance, correlational studies have identified the contribution of local parks to the development of social ties in inner-city neighborhoods (Kazmierczak, 2013), which are
related to better life quality. Experimentally creating online social environments can potentially lead to different network formations that further direct behavior change dynamics. In this dissertation, social incentives were fixed on constructed online networks. Future research can explore whether putting individuals into supportive or competitive environments can systematically alter their choices in establishing connections and sharing certain information with other people. Such experiments require clustered randomized design to replicate the network formation processes. Allowing individuals to alter their network connections assists them in adapting their behavior change goals and can potentially increase their engagement in the long term.

Applications to Other Behavior Change Domains and Populations

This dissertation focuses on physical activity among young adults. Future research can apply this research approach in other behavior change domains. Characteristics of health behaviors vary a lot and range from public to private, one-time to lifelong, and easy to difficult. Physical activity is often public and difficult to engage consistently for a long time. Smoking or drug use is often private and difficult to quit. In contrast, adopting a vaccination can be public or private depending on the topic and relatively easy to adopt at one time. Sexual behavior is highly private and attached with many social stereotypes or stigmatization. Online network intervention designs need careful calibrations to address different behavior characteristics. The strong effects of competitive online networks seem intuitive for physical activity promotion but less so for sexual risk reduction, which decision is more complex and relies on changes in individuals’ risk perceptions, attitudes, and behavior control. Past research has shown
people’s sexual risk behaviors and women’s reproductive behavioral decisions are clustered within their social networks (Bond, Valente, & Kendall, 1999; Chen et al., 2016). It remains to be seen how we could harness the power of online networks in leveraging social influence to change private and sensitive behaviors. For such topics, anonymity should be a design priority while keeping behavior signals relevant and trustable.

Similarly, the online network approach needs to be tested in other populations. The dissertation studies only involved healthy young adults, who are generally more competitive. For patient populations with chronic diseases in need of social support, competing with others especially strangers or being influenced by social norms may be less relevant. To what extent social influence and online networks can contribute to behavior change among such populations remains an important empirical question.

Although a lot of patient online forums focusing on chronic illnesses such as diabetes, breast cancer, and HIV have millions of users, their uses are centered mostly on informational or emotional support (Eysenbach et al., 2004). Introducing online networks that update on these users about their peers’ medication adherence may be a meaningful direction. Currently most medication adherence apps employ reminders as the main strategy (Dayer, Heldenbrand, Anderson, Gubbins, & Martin, 2013). Knowing others’ medication intake through anonymous online networks may serve as good reminders and encouragements that eventually improve patients’ medication adherence.
Implications

Results of this dissertation are located within the context of online network-based health interventions. This dissertation suggests a general approach to using online networks to improve public health. Healthcare providers, online fitness programs, and peer-to-peer communities for improving public health all seek ways to structure social interactions among their members to provide the greatest incentives for adopting and maintaining positive health behaviors. The study results suggest that online networks composed of similar strangers that continuously update each individual on peers’ positive behaviors can be effective for motivating desirable behaviors. The networks rely on sending positive behavior signals and highlighting others’ achievement to stimulate the social influence dynamics. While individuals can indeed benefit from behavior tracking technologies, it is the online networks that can eventually build upon individuals’ behavior change efforts and sustain the population-level behavior change in the long term. As people’s normative perceptions get shifted and consolidated, previously deemed hard-to-reach or uncommon behaviors can eventually become the new social norm.

Public health programs that focus on improving preventive behaviors can harness the online networks to communicate positive behavior change signals to network members. Simple health messages can reach all network members relatively fast. However, actual behavior change requires repeated exposures to other people’s positive behavior signals. On the other hand, programs that target on negative behavior refraining such as smoking cessation should not simply replicate this intervention approach. Instead, such programs need to consider which behavior signals can be relayed. With careful
design, behavior refraining can also be translated into a meaningful digital behavior signal.

**Conclusion**

Online network is an established and growing source of health communication and intervention for the public. The findings from this research provide the first step toward uncovering the impact of online networks as a unique form of intervention on young adults’ physical activity behavior. Showing its efficacy on physical activity proves this approach’s feasibility and utility. Online networks have great potential to influence a range of health-behavior changes and decisions. More research is needed to fully understand the long-term effects of different network configurations on different behaviors. As online technologies rapidly involve, uncovering theoretical mechanisms that mediate the network influence becomes more important than ever before in addressing many public health challenges.
APPENDIX

PennFit Online Post-Assessment Survey

3/19/2016
Qualtrics Survey Software

Default Question Block

The purpose of this survey is to understand your exercise behaviors after you have used the PennFit app for a month. Please answer the questions honestly and accurately. All of your answers will be kept in strictest confidence. Your name will not be on the survey. Instead, we will give you a computer-generated code number. Thank you.

1. What is your personal email address?

2. What is your assigned PennFit gmail address?

3. What is your height? (in feet and inches)

4. What is your weight? (in lbs)

5. What is your favorite exercise?

6. In general, how would you rate your overall quality of life?
   - Poor


1/10
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The next two questions refer to the drawing of the ladder below representing the "Ladder of Life." The top of the ladder (9) represents the best possible life for you. The bottom of the ladder (1) represents the worst possible life for you.

7. On which step of the ladder do you feel you personally stand at the present time?

8. Thinking about your future, on which step do you think you will stand about one year from now?

Please select how often you did each of the following behaviors in the PAST 7 DAYS.

9. On how many of the past 7 days, did you exercise or participate in vigorous physical activity for at least 20 minutes that made you sweat and breathe hard, such as basketball, soccer, running, swimming laps, fast bicycling, fast dancing, or similar vigorous physical activities?

- 0 days
- 1 day
- 2 days
- 3 days
- 4 days
- 5 days
10. On how many of the past 7 days, did you exercise or participate in moderate physical activity for at least 30 minutes that did not make you sweat and breathe hard, such as walking, slow bicycling, skating, pushing a lawn mower or anything else that caused small increases in breathing or heart rate?

- 0 days
- 1 day
- 2 days
- 3 days
- 4 days
- 5 days
- 6 days
- 7 days

11. On how many of the past 7 days, did you exercise to strengthen or tone your muscles, such as push-ups, sit-ups, or weight lifting?

- 0 days
- 1 day
- 2 days
- 3 days
- 4 days
- 5 days
- 6 days
- 7 days

12. How many of your 5 closest friends exercise for 2 hours and 30 minutes (150 minutes) of moderate aerobic activity (i.e., brisk walking) OR 1 hour and 15 minutes (75 minutes) of vigorous aerobic activity (i.e., jogging or running) every week?

- 0
- 1
- 2
- 3
- 4
- 5
13. How many of your 5 closest friends do muscle strengthening exercises such as push-ups, sit-ups, or weight lifting at least 2 days a week?

- 0
- 1
- 2
- 3
- 4
- 5

14. How bad or good would it be to exercise for 30 minutes at least 5 times a week in the next month?

- Very bad
- Bad
- In the middle
- Good
- Very good

15. How foolish or wise would it be to exercise for 30 minutes at least 5 times a week in the next month?

- Very foolish
- Foolish
- In the middle
- Wise
- Very wise

16. How unpleasant or pleasant would it be to exercise for 30 minutes at least 5 times a week in the next month?

- Very unpleasant
- Unpleasant
- In the middle
- Pleasant
- Very pleasant

17. How dangerous or safe would it be to exercise for 30 minutes at least 5 times a week in the next month?
18. How harmful or beneficial would it be to exercise for 30 minutes at least 5 times a week in the next month?

- Very harmful
- Harmful
- In the middle
- Beneficial
- Very beneficial

19. Most people who are important to me would think it is okay for me to exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

20. Most people who are important to me would think I should exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

21. Most people who are important to me would want me to exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
22. I am confident that I can overcome obstacles that might prevent me from exercising for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

23. I am sure that I can exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

24. I plan to exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

25. My goal is to exercise for 30 minutes at least 5 times a week in the next month.

- Disagree strongly
- Disagree
- In the middle
- Agree
26. I will try to exercise for 30 minutes at least 5 times a week in the next month.
   - Disagree strongly
   - Disagree
   - In the middle
   - Agree
   - Agree strongly

For the next question, think about your friends and other African American women in your age. We recognize that you may not know for sure about their health behavior. However, please give us your impressions or best guess of their behavior.

27. Most African American women in my age exercise for 30 minutes at least 5 times a week.
   - Disagree strongly
   - Disagree
   - In the middle
   - Agree
   - Agree strongly

28. Most of my friends exercise for 30 minutes at least 5 times a week.
   - Disagree strongly
   - Disagree
   - In the middle
   - Agree
   - Agree strongly

29. Most PennFit participants exercise for 30 minutes at least 5 times a week.
   - Disagree strongly
   - Disagree
   - In the middle
   - Agree
30. Below is a list of things friends or acquaintances might do or say to you. Rate how often your friends or acquaintances have said or done what is described during the past month. The left end is "Never" and the right end is "Very often."

**During the past month, my friends or acquaintances:**

<table>
<thead>
<tr>
<th>Activity</th>
<th>Never</th>
<th>Rarely</th>
<th>A few times</th>
<th>Often</th>
<th>Very often</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exercised with me.</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offered to exercise with me.</td>
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</tr>
<tr>
<td>Gave me helpful reminders to exercise (&quot;Are you going to exercise tonight?).</td>
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<tr>
<td>Gave me encouragement to stick with my exercise program.</td>
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<tr>
<td>Changed their schedule so we could exercise together.</td>
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</tr>
<tr>
<td>Discussed exercise with me.</td>
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<tr>
<td>Complained about the time I spend exercising.</td>
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<tr>
<td>Criticized me or made fun of me for exercising.</td>
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<tr>
<td>Gave me rewards for exercising (bought me something or gave me something I like).</td>
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<tr>
<td>Planned for exercise on recreational outings.</td>
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<tr>
<td>Helped plan activities around my exercise.</td>
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<td></td>
</tr>
<tr>
<td>Asked me for ideas on how they can get more exercise.</td>
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</tbody>
</table>

31. Do you know other women participating in PennFit?

- No
- Yes

31a. Please write down their names ("write down all the names that you know.")

32. I feel supported by other PennFit participants to exercise.

33. I want to beat other participants' PennFit scores.
- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

34. I feel pressured by other participants to increase my PennFit score.
- Disagree strongly
- Disagree
- In the middle
- Agree
- Agree strongly

35. On a scale from 0-10, how likely are you to recommend PennFit to a friend or colleague?

<table>
<thead>
<tr>
<th>Not at all likely</th>
<th>Extremely likely</th>
</tr>
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</table>

36. On a scale from 0-10, how much do you like PennFit?

<table>
<thead>
<tr>
<th>Not at all likely</th>
<th>Extremely likely</th>
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</table>

37. Thinking about the PennFit app... About how often do you use it?
- Several times a day

38. In what ways has PennFit changed your lifestyle?

39. Do you have any comments or suggestions for us to improve PennFit in the future?


Williams, S. L., & French, D. P. . (2011). What are the most effective intervention techniques for changing physical activity self-efficacy and physical activity behaviour—and are they the same? *Health Education Research, 26*(2), 308-322.


