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Complementary Support from Facilitators and Peers for Promoting mHealth Engagement and Weight Loss

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This study investigates the effects of mHealth interventions on sustainable behavior change and weight loss, drawing on in-app user activity data and online survey data. Specifically, we focus on the interactions within mobile support groups in Noom, an mHealth application for obesity intervention, to delve into how social support from facilitators and peers may play differential roles in promoting health outcomes. The results of structural equation modeling (N = 301) demonstrated that (a) perceived facilitator support was positively associated with group members' health information acquisition such as fitness-themed article reading whereas perceived peer support was positively linked to group participation such as posting and responding; (b) perceived peer support was positively related to normative influence among group members, which subsequently increased group members' responses to others' posts; and (c) health information reading and in-group posting promoted weight loss; however, merely responding to others' posts did not lead to weight-loss success. The findings suggest that the complementary influences of facilitators and peers must be considered to enhance the efficacy of support group interventions.

The prevalence of obesity is one of the most critical public health threats in the United States. Obesity is associated with elevated risks for a multitude of health problems such as diabetes, various types of cancer, stroke, hypertension, and other cardiovascular diseases (Vucenik & Stains, 2012). Obese individuals are also highly likely to face concomitant financial consequences. The annual health care costs showed a J-curve relationship with body mass index (BMI): in fact, obese adults spend 3,508 dollars more annually in medical costs than those who maintain a healthy weight (Cawley, Meyerhoefer, Biener, Hammer, & Wintfeld, 2015). However, despite the well-known repercussions of obesity, recent statistics reported that the obesity rate had continued to increase from 1999 through 2014, reaching approximately 36.5% of all adults (Ogden, Carroll, Fryar, & Flegal, 2015).

It is thus unsurprising that Americans invest substantial resources in a variety of weight-loss programs. One recent advancement in this area is mHealth (or mobile health) technology for weight-loss interventions. Weight-loss mHealth applications offer a range of features such as weight trackers, food and physical activity logging, reward systems, and health news delivery, all of which are essentially geared toward promoting self-regulation of dietary behavior (Zahry, Cheng, & Peng, 2016). However, to sustain self-monitoring tasks, it is crucial for individuals to obtain necessary social support since a weight-loss process often requires considerable long-term efforts that may not lead to immediate outcomes (Kim, Faw, & Michaelides, 2017). Yet social support exchange in mHealth environments has received limited empirical attention. More importantly, prior scholarship on the effects of mediated social support focuses primarily on psychological outcomes based on self-report, such as perceived depression or quality of life (for a review, see Rains & Wright, 2016; Rains & Young, 2009). Given that mHealth applications enable researchers to obtain behavioral data (e.g., food logs, footsteps, or posts) without relying on self-reports, mHealth environments extend a promising scholarly potential for demonstrating relationships between social support and behavioral outcomes. Although mHealth applications have become increasingly popular, research on the role of social support in mHealth engagement and accompanied health outcomes is still nascent (Aikens, Trivedi, Heapy, Pfeiffer, & Piette, 2015; Kim et al., 2017).

Addressing this gap, this retrospective study examines the influences of social support exchange within mobile groups (built in an mHealth application) on behavior change and weight loss, drawing on both survey data and in-app user activity data. In particular, this study focuses on the use of Noom, an mHealth application for weight loss that offers a variety of features such as food logging, health article delivery, and mobile groups. In mobile groups, users exchange social support with facilitators and peer members. Group facilitators share advice, suggestions, and diet-related information to group members. They can set up health goals for the group and assist members to achieve the goal. Also, group members encourage each other to continue to invest in weight-loss effort through exchanging posts, comments, and "hearts." Thus, Noom serves as an ideal research context to investigate different support roles and users' behavior in mobile group settings. In the next section, prior work on social support, behavior change, and weight loss will be reviewed.

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The Role of Mediated Social Support in Behavior Change and Weight Loss

Social support has been defined as verbal and nonverbal communication that "reduces uncertainty about the situation, the self, the other, or the relationship, and functions to enhance a perception of personal control in one's life experience" (Albrecht & Adelman, 1987, p. 19). Its functions to decrease uncertainty and promote the ability to exert control over one's life and surroundings have been extensively studied in health contexts. For example, diabetes patients who perceived greater support from online communities showed a significantly enhanced sense of empowerment (Oh & Lee, 2012). Also, perceived support was associated with lower stress, less physical illness, and greater well-being (Nabi, Prestin, & So, 2013). Given the critical role of social support in health promotion, social support scholarship has investigated different medical conditions to elucidate how researchers can harness the influences of social support to advance intervention strategies.

Specifically, social support can be a substantial help for accomplishing weight-loss goals, which involves long-term self-management practices (Elfhag & Rössner, 2005; Livhits et al., 2011; Turner-McGrievy & Tate, 2013). As online interactions have become part of day-to-day routines, both researchers and practitioners have incorporated various online or mobile group features into obesity interventions using online communities (Harvey-Berino, Pintauro, Buzzell, & Gold, 2004), social media (Ballantine & Stephenson, 2011), interactive websites (Stevens et al., 2008), and text messaging (Napolitano, Hayes, Bennett, Ives, & Foster, 2013), revealing the benefits of mediated social support for sustaining weight loss.

Taking a closer look at mediated support groups, scholars have examined the influences of social support from facilitators on weight-loss outcomes, in conjunction with peer-to-peer social support. For example, individuals assigned to online discussion groups facilitated by group therapists sustained weight loss over 18 months at a rate comparable to individuals who had regular face-to-face meetings (Harvey-Berino et al., 2004). Also, individuals who regularly received messages from intervention coordinators and designated support providers lost significantly greater weight than others who only had access to support groups (Napolitano et al., 2013). Further, in comparison to peer-to-peer exchanges, counselors were more likely to provide nutrition and weight-loss-related information, and also more likely to solicit suggestions from members about other needed information (Hales, Davidson, & Turner-McGrievy, 2014). Noom's facilitators also share information regarding weight loss and encourage members to engage in learning about healthy lifestyle behaviors. Hence, group members who perceive a greater amount of facilitator support are more likely to engage in learning fitness-related information. As a range of fitness-themed articles (e.g., nutrition information, physical activity suggestions) are offered in Noom and members access them to a varying extent, we propose the following hypothesis to ascertain the influence of facilitator support on health information reading behavior:

Hypothesis 1: Perceived facilitator support is positively associated with the number of health articles read in Noom.

In addition, a cumulative body of research has delved into the benefits of online peer support and their influences on group participation. Specifically, individuals with chronic illness increasingly participate in online communities, seeking others with similar experiences, objective feedback, and a shelter to exchange their feelings without the fear of judgment (Wright & Bell, 2003; Wright & Rains, 2013). Indeed, perceived similarity with group members enhanced the satisfaction with online social support, which was positively associated with group participation (Wright, 1999, 2000a, 2000b). A meta-analysis of the outcomes of online support also confirmed that perceived support from computer-mediated support groups was positively associated with group participation (Rains & Young, 2009). Furthermore, when groups consist of less intimate relationships that are assumed to exist for a specified length of time, group members tend to feel obliged to reciprocate the support offered by their peers. This subsequently increases group contribution behavior (Chan & Li, 2010; Clark, 1984). In this vein, we propose that the members of Noom groups who perceive greater peer support are more likely to participate in group interactions, as represented by the number of original posts and comments to others. This relationship is presented in the following hypothesis:

Hypothesis 2: Perceived peer support is positively associated with (a) the number of original posts and (b) the number of responses to others in a Noom group.

Furthermore, group members who perceive greater peer support are likely more subject to the normative influence of their peers. Normative influence refers to the extent to which a person tends to conform to positive expectations of others (Burnkrant & Cousineau, 1975). Especially in group settings, individuals may feel pressured into engaging in a desired behavior due to perceived threats (e.g., social judgment or interpersonal sanctions) or perceived benefits (e.g., social acceptance) (Gibbs, Kim, & Ki, 2016; Rimal & Real, 2003). In line with the reciprocity norms discussed above, receiving support can create a sense of accountability to the supporter (Belgrave & Moorman Lewis, 1994), increasing the susceptibility to peer influence. Particularly in the context of health interventions, prior work has consistently found that social support is tied to adherence to medical treatments (for a review, see DiMatteo, 2004). Thus, Noom users who perceive more support from peers may feel more invested in their weight-loss groups and, in turn, strive to meet others' expectations such as following suggested dietary choices. We hence hypothesize as below:

Hypothesis 3: Perceived peer support is positively associated with perceived normative influence from peers.

In turn, we propound that perceived normative influence is positively related to the number of responses to other users' messages in a mobile group. Prior research has shown that group norms influence interactions in mediated contexts (Lee & Nass, 2002), such as instant messaging (Shen et al., 2011) and virtual communities (Dholakia, Bagozzi, & Pearo, 2004). A long-standing literature on online communities has also demonstrated that normative influence has a positive effect on group identity and participation intention (Dholakia et al., 2004), as well as group participation (Zhou, 2011). Namely, group members who are susceptible to peer influence are more likely to show conformity behavior by engaging with others' activities. Therefore, we propose the following hypothesis:

Hypothesis 4: Perceived normative influence from peers is positively associated with the number of responses to others in a mobile group.

We also examine the relationships between Noom users' in-app activities such as reading fitness-themed articles, uploading posts, and responding to others' posts. We suggest that reading health-related online articles is an in-app activity with the lowest entry barrier that requires relatively less effort. However, reading behavior may subsequently lead to further online engagement. In fact, prior research has reported that a majority of online users merely observe others' activities or read online articles (i.e., lurking), whereas only a subset of individuals contribute original posts to online communities (Hwang et al., 2011). However, once users are involved in regular reading, they begin to engage in group activities by sharing their own posts. For example, in weight-loss intervention studies, 28% of participants posted to the discussion board (Tate, Wing, & Winett, 2001) and 19% of participants started new discussion threads on a daily basis (Hwang et al., 2010). In turn, active posters in health-related support groups are also likely to respond to messages uploaded by others (Ballantine & Stephenson, 2011). Given this tendency, we propose that the members who read a greater number of online articles are more likely to contribute their own posts. Next, we also posit that the number of original posts is positively associated with the number of responses to others. Overall, the levels of in-app user activities are positively related to each other. The relationships are hypothesized as follows:

Hypothesis 5: The number of articles read is positively associated with the number of original posts in a mobile group.

Hypothesis 6: The number of original posts in a mobile group is positively associated with the number of responses in a mobile group.

The three variables that represent participation activities in Noom—the number of articles read, the number of original posts, and the number of responses to others' posts—indicate the different degrees of behavior change among Noom users. Although reading health-related articles may be viewed as a passive activity compared with posting and responding, all three activities signal behavioral engagement with an mHealth intervention: health information acquisition group contribution. Since Noom aims to increase the levels of various app-enabled activities, which may lead to continued engagement in weight-loss efforts, sustained mobile group participation signals users' involvement in weight-loss programs. Further, several studies have shown that individuals take actions following health information obtained online (for a review, see Hu & Sundar, 2010). Along these lines, prior work also revealed that participation rates in online groups were tied to behaviors leading to weight loss (Hwang et al., 2011). Namely, the more users engage in mHealth interventions, the more likely they achieve their weight-loss goals. Therefore, we put forth the following hypothesis:

Hypothesis 7: (a) The number of articles read, (b) the number of original posts, and (c) the number of responses to others are positively associated with weight loss.

Overall, this study investigates whether and how social support from different providers such as facilitators and peer group members is associated with users' in-app activities, which indicate behavior change. Subsequently, this study ascertains the relationships between various in-app activities and weight-loss outcomes (see Figure 1).

Methods

Research Context

Noom is a commercial mHealth application for lifestyle intervention for weight loss. As part of registration, Noom users provide basic profile information, such as their purpose of use, past diet experiences, weight, height, gender, and age. The information is used to generate a proprietary algorithm that

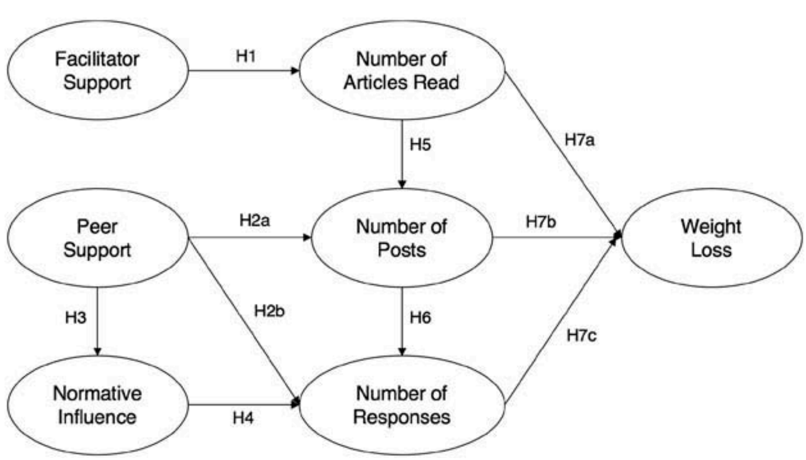

Fig. 1. Hypothesized model.

clusters users into different mobile groups, compute BMI, and recommend daily calorie intake as well as relevant articles on fitness and nutrition. In Noom groups, individuals can asynchronously upload their posts and monitor others' updates. They can respond to others' posts or click "hearts" to interact with one another and convey support.

As of 2015, each Noom group consisted of one group facilitator and 6–12 members. Facilitators were selected from volunteers who successfully achieved their weight-loss goals through Noom use and completed training sessions for group facilitation and coaching. Facilitators were thus viewed as role models who already acquired necessary skills and knowledge for weight loss and continued to maintain a healthy weight. Although their roles were not codified, some responsibilities include providing advice and information, suggesting new daily tasks, and answering questions. In sum, the facilitator program was developed to address the limitations of peer-only groups where members did not have appropriate knowledge and efficacy to initiate behavior change and subsequently struggle to accomplish their health goals.

Procedure

Upon IRB approval from authors' institution, the initial sample pool was generated in May 2015 as follows. We targeted all adult Noom users in the United States, using the duration of Noom use (6 months) and group enrollment as inclusion criteria. The duration of use was a particularly important sampling restriction for two reasons. First, we selected newly registered users who had sustained their membership for 6 months to control the time frame, which could affect the outcomes of Noom use. Second, this restriction allowed us to compare weight change in two different time points (registration and post 6 months). To ensure the data quality, we excluded users (a) who did not record their weight in time point 2 or (b) who never participated in group activities. Based on these sampling criteria, a random sample of 2,877 users was extracted directly from Noom's database. All participants were self-enrolled in a Noom group for six consecutive months between April 2014 and April 2015.

An online survey hosted on Qualtrics was distributed by the first author to all 2,877 users from May to June 2015. An online consent form was provided to inform participants that the study was confidential, participation was voluntary, and that individual responses would not be disclosed. To compensate for their participation, all respondents who had completed the survey were provided with a 1-month free subscription for Noom. Additionally, they were entered into a raffle to win 1 of 10 Amazon e-gift certificates ($50 each). A total of 301 participants completed the survey, yielding a 10.5% response rate. Given that surveys targeting the general public of American adults typically achieve response rates of 9% (Kohut, Keeter, Doherty, Dimock, & Christian, 2012), the present study reached a slightly higher response rate compared with surveys distributed to the general public.

In conjunction with the online survey, in-app user activity data were downloaded from the Noom server as evidence of behavior/weight change. Noom did not store any personal information except gender and age at the time of data collection. The user behavior data included the number of articles read, original posts, and responses to others (i.e., comments and hearts). All user behavior data were limited to the 6-month period, corresponding to the reference point for weight change. Weight change was assessed based on initial weight (time 1) and weight after 6 months of Noom use (time 2). This big data set consisted of 561,287 total number of articles read, 57,205 original posts, 82,697 comments, and 53,100 hearts.

Measures

Perceived Facilitator and Peer Support

We employed an adapted version of the Medical Outcomes Study social support scale (Sherbourne & Stewart, 1991) to measure perceived facilitator support and perceived peer support. The scale was designed as a comprehensive measure that examines the multidimensional aspects of social support that encompasses emotional, informational, tangible, and affectionate support. Given that mobile groups in Noom were loosely knit networks operating solely online, we concentrated on the informational and emotional aspects of social support rather than tangible and affectionate support, which created an eight-item scale. Participants were asked to rate each statement based on a five-point Likert-type scale ranging from 1 = *strongly disagree* to 5 = *strongly agree*. As for perceived facilitator support, sample items include "Facilitator tries to give information to help me understand health-related situations" and "Facilitator tries to give good advice about a health-related crisis" ($M = 3.18$, $SD = 1.05$, $\alpha = .96$). Sample items for perceived peer support include "I can count on my group members to listen to me when I need to talk" and "I can confide in or talk to my group members about myself or my problems" ($M = 3.22$, $SD = 1.03$, $\alpha = .96$). After performing a confirmatory factor analysis (CFA), one item was removed from each scale (χ^2/df = 2.40, comparative fit index [CFI] = .97, standardized root mean square residual S[RMR] = .04, root mean square error of approximation [RMSEA] = .06).

Normative Influence

Drawing on extant literatures, an original scale was created to assess peer pressures that individuals experience to conform to perceived codes of conduct (Real & Rimal, 2007; Rimal & Real, 2003). Given the context of weight loss, we were interested particularly in injunctive norms that exert social influence on group members' dietary behavior. Sample items include "I generally select meals/snacks that I think my group will approve of" and "I care a lot about what my group members want me to do when making dietary decisions." A total of five statements were rated based on a five-point Likert-type scale ranging from 1 = *strongly disagree* to 5 = *strongly agree* ($M = 2.93$, $SD = 1.00$, $\alpha = .91$). Based on CFA results, one item was removed (χ^2/df = 2.49, CFI = .97, SRMR = .03, RMSEA = .07).

Behavioral Variables

Server-level data were analyzed to assess the levels of participants' in-app activities, which indicate their sustained behavioral engagement during the study time frame. First, participants engaged in health information acquisition by reading fitness-themed articles provided by Noom. The total number of articles read refers to not merely clicking behavior but actually "marking" the article as "read" (M = 276.61, SD = 252.71). Second, we also obtained key variables that signal participants' group engagement. Users can upload their posts (e.g., status updates, food diaries/photos, or personal health goals) to the group as part of daily tasks. Additionally, if users desire to interact with other members further, they can also leave comments or "hearts." Original posting behavior was operationalized by the number of original posts (M = 50.73, SD = 90.67), whereas responding behavior was assessed by the sum of the numbers of comments and hearts (M = 127.39, SD = 341.99).

Weight Loss

Weight loss was operationalized by the change in BMI, which is individuals' weight in kilograms divided by their height in meters squared (kg/m^2). Individuals with a BMI greater than 30 are considered clinically obese whereas those with a BMI ranging from 25 to 29.9 are considered clinically overweight. A BMI of 18.5–24.9 indicates a healthy weight. The change in BMI was computed drawing on the data in time point 1 (registration date) and time point 2 (post 6 months) (M = 1.01, SD = 2.32). Positive values of BMI change indicate weight-loss success, whereas negative values represent weight gain.

Analysis

Preliminary Analyses

As a first step, we computed descriptive statistics of main variables (see Table 1). Descriptive statistics showed that the variables obtained from users' in-app activities were positively skewed, reflecting the power law that is commonly observed in the distribution of online user activities: only a small number of active users account for the generation of most online content (Barabasi & Reka, 1999). Like any other online platforms, most users were "lurkers" or less active users, whereas a relatively small number of users generated and received most of the posts.

Table 1. Participant demographics and descriptive statistics (N = 301)

Characteristic	Mean or %	SD
Age	34.74	10.82
Gender		
Women (%)	73.2	
Height (cm)	168.5	8.99
Weight at time 1 (kg)[a]	91.91	18.94
Weight at time 2 (kg)[b]	89.03	18.91
BMI at time 1 (kg/m^2)	32.32	5.98
BMI at time 2 (kg/m^2)	31.31	7.08
BMI change (kg/m^2)[c]	1.01	2.32
Number of articles read	276.61	252.71
Number of posts	50.73	90.67
Number or comments	71.06	194.72
Number of hearts	56.33	155.64

[a]Registration.
[b] Post 6 months.
[c] Positive values indicate weight-loss success.

Table 2. Bivariate correlations among study variables

Variable	1	2	3	4	5	6
1. Facilitator support						
2. Peer support	.50**					
3. Normative influence	.32**	.44*				
4. Number of articles read	.12*	.07	.02			
5. Number of posts	.18*	.16**	.38**	.38**		
6. Number of responses	.25**	.24**	.24**	.24**	.53**	
7. BMI change	.07	.06	.28**	.28**	.34**	.18**

*$p < .05$. **$p < .01$.

As the values of those variables included positive data ranging from 0 to 3,711, all variables were normalized using square root transformation before conducting further analyses. Also, bivariate correlations among all variables were performed using the normalized values (see Table 2).

Substantive Analyses

To test our hypothesized model, we conducted maximum likelihood structural equation modeling (SEM) using AMOS version 22. SEM has been viewed as an integrative and rigorous way to evaluate the underlying structure of both a measurement and theoretical model. Namely, SEM allows researchers to ascertain the relationships between observations and latent variables, as well as the associations between latent constructs. The analysis results will ultimately demonstrate whether the proposed model fits observed data. The model fit was determined based on multiple goodness-of-fit indices: (a) the chi-square to the degrees of freedom ratio (χ^2/df) is less than 3; (b) the CFI is higher than .95; (c) the SRMR is less than .07; and (d) the RMSEA is .07 or less (Hu & Bentler, 1995; Kline, 2015; Steiger, 2007).

Results

The results of SEM demonstrated that goodness-of-fit indices of the hypothesized model were within an acceptable range: χ^2/df = 2.63, CFI = .94, SRMR = .05, RMSEA = .07. However, a path from responses to others to weight loss (Hypothesis 7c) was not significant (p = .38). This may indicate that simply leaving a reply or heart to others does not necessarily contribute to weight loss, in comparison with other in-app activities that directly reflect one's change in their own behavior. The path was hence removed from the model before conducting further analysis. The final model revealed a slightly improved fit for the data: χ^2/df = 2.27, CFI = .95, SRMR = .05, RMSEA = .06. All path coefficients included in the final model were significant. Perceived facilitator support was positively associated with the number of articles read in Noom (Hypothesis 1) and perceived peer support was positively linked to both the number of original posts (Hypothesis 2a) and the number of responses to others in a mobile group (Hypothesis 2b). Perceived peer support was also positively related to perceived normative influence of group members (Hypothesis 3), which in turn led to an increased

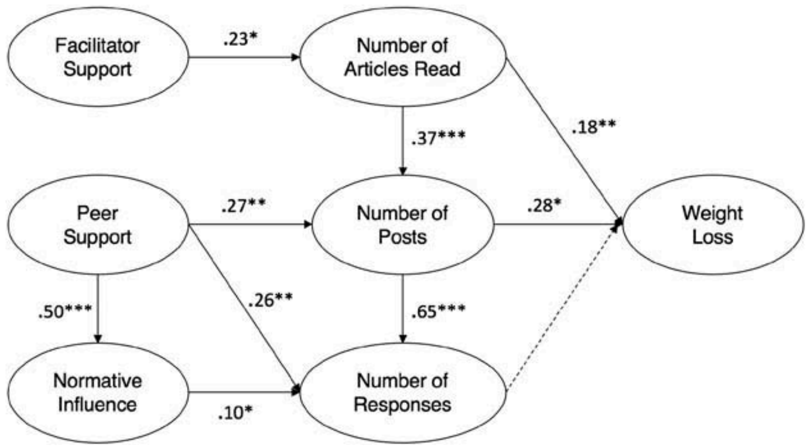

Fig. 2. Final empirical model. $\chi^2/df = 2.27$, CFI = .95, SRMR = .05, RMSEA = .06.

number of responses to others (Hypothesis 4). In addition, participants' in-app activities had positive relationships with one another. Users who read more health-related articles were more likely to contribute more posts to their mobile group (Hypothesis 5), which was also positively associated with greater engagement with other members' posts (Hypothesis 6). Finally, the numbers of articles read and original posts created were positively linked to weight-loss success (Hypotheses 7a and 7b); however, leaving responses for others did not necessarily promote weight loss (Hypothesis 7c). In aggregate, all hypotheses were supported except Hypothesis 7c (see Figure 2).

Discussion

This study investigated a mobile support group implemented in Noom to shed light on how intervention design may harness the complementary influences of facilitator support and peer support. The results demonstrated that perceived support from mobile groups significantly promoted users' mHealth engagement and weight loss. Specifically, (a) facilitator support was associated with health information acquisition (i.e., health-related article reading), whereas peer support was related to group participation (i.e., posting and responding); (b) peer-based normative influence, in tandem with peer-based social support, also enhanced mHealth engagement; and (c) both health article reading and group participation were positively linked to weight loss. In sum, the findings corroborate the clinical efficacy of mobile groups in the context of weight-loss interventions, extending an array of theoretical and practical implications.

First, this study contributes to social support scholarship by ascertaining the direct associations between perceived support and behavioral variables. Although perceived support has been widely studied across disciplines, its health outcomes have been operationalized primarily as self-reported measures of psychological conditions such as perceived stress or subjective well-being. Scholars have voiced their concerns over this trend due to conceptual and methodological overlaps between perceived support and perceived outcome variables (Barrera, 1986; Gore, 1981; Kim, 2014). Drawing on in-app user activity data, we took an alternative approach to test whether perceived support has a relationship with actual behavior change. The findings revealed that perceived support was positively related to behavioral engagement with Noom, which subsequently promoted weight-loss success. To unravel the multifaceted influences of supportive interactions, it is important to examine their effects on not only perceived mental health outcomes but also various behavioral measures. As technology-enabled interventions enable researchers to collect participants' communicative interaction data, researchers should investigate behavioral patterns that can be shaped by social support exchange. Exploring the associations between different types of social support and behavioral measures will advance social support theory and research by demonstrating mechanisms through which social support promote various health outcomes.

Second, this study made a distinction between facilitator support and peer support, revealing that they played differential roles in promoting group members' mHealth engagement. Indeed, when part of formal interventions, mediated support groups often have assigned therapists, counselors, or facilitators and provide both educational and interactional features (Rains & Young, 2009). Nevertheless, prior work on support groups has not differentiated facilitator-driven support from peer-driven support, treating supportive transactions available within an online group as unidimensional (Eysenbach, Powell, Englesakis, Rizo, & Stern, 2004). By assessing group members' differential perceptions of facilitator support and peer support, this study showed that facilitator and peer support had complementary effects on enhancing mHealth use. The users who perceived a higher level of facilitator support were more likely to access and read health-related articles in Noom, indicating a greater level of health information acquisition. By contrast, perceived peer support was positively related to users' mobile group activities for a sustained 6-month period. This finding signals that support from peers is a critical factor for member retention and continued participation in group activities. Given that both informational and relational dimensions of social support may jointly contribute to health outcomes, the educational and social roles of different support providers must be further examined. As interactions with various support providers (e.g., caregivers, doctors, support group members) may shape intervention outcomes, it is critical to investigate their differential influences on social support processes.

Third, by highlighting the communicative dimensions of mHealth interventions, we delineated that group participation behaviors could account for weight-loss outcomes. Although the efficacy of mHealth engagement is a burgeoning area of research, extant literatures primarily deal with task-oriented in-app activities directly pertaining to health-related behavior (e.g., physical activity logging, food logging) to understand the effects of mHealth interventions on weight loss. However, relational and communicative dynamics may also help users enact behavior change, adhere to interventions, and continue to use mHealth applications. Especially given that mHealth applications often adopt group features to assist their users, the effects of communicative interactions on health outcomes should be further examined to better utilize group-based or communicative features. In the current study, we showed that sustained in-group interactions for a 6-month period significantly contributed to weight loss, indicating that communicative exchanges within mHealth applications reflect sustained behavior change.

Finally, our findings also yield important practical implications for advancing health intervention design: mHealth developers should consider (a) incorporating various communicative features into their application design to reinforce relational interactions among users and (b) assigning facilitators or coaches when possible rather than simply providing a venue for peer-to-peer interactions. Since relying solely on self-monitoring features is not sufficient to sustain compliance behavior (Kim et al., 2017), practitioners should include other methods to exert peer support and influence when in-person/direct observations are not feasible. Also, mHealth applications may benefit from assigning facilitator roles to members (e.g., volunteers among users who already successfully achieved their weight-loss goals) given that having a facilitator can offer a distinctive advantage for enacting behavior change. By fostering social and relational exchanges through mHealth applications, practitioners can utilize the power of support groups where members encourage each other to initiate lifestyle change, surmount diverse obstacles, and adhere to intervention programs. In sum, when incorporating communicative features into mHealth design, different influences of facilitator- and peer-driven support must be considered to enhance the efficacy of interventions.

Limitations and Future Directions

We acknowledge that this study is not without limitations. First, although we paid attention to posting and responding activities within mobile groups, we did not analyze the actual content of group interactions. We were not able to obtain the access to communications in mobile groups in part because of health-related privacy concerns. Future research could benefit from content analysis to generate an in-depth knowledge of the types and characteristics of social support transactions that occur through mobile platforms. Given the nature of in-app communication (e.g., brevity, multimedia content), the analysis of mobile content will provide significant insight into mHealth-enabled supportive communication, which may portray distinctive patterns in comparison to online support communities where lengthy narratives can be uploaded. Second, although this study demonstrated the influence of group activities on health promotion, its standardized path coefficient indicated a relatively small effect. Despite the significance of establishing the connections between communicative interactions and weight-loss outcomes, future studies should conduct a comparative analysis to elaborate on the efficacy levels of various mHealth features such as physical activity tracking and calorie counting, drawing on a comprehensive data set.

References

Aikens, J. E., Trivedi, R., Heapy, A., Pfeiffer, P. N., & Piette, J. D. (2015). Potential impact of incorporating a patient-selected support person into mHealth for depression. *Journal of General Internal Medicine*, *30*, 797–803. doi:10.1007/s11606-015-3208-7

Albrecht, T. L., & Adelman, M. B. (1987). *Communicating social support*. Newbury Park, CA: Sage.

Ballantine, P. W., & Stephenson, R. J. (2011). Help me, I'm fat! Social support in online weight loss networks. *Journal of Consumer Behaviour*, *10*, 332–337. doi:10.1002/cb.374

Barabasi, A.-L., & Reka, A. (1999). Emergence of scaling in random networks. *Science*, *286*, 509–512. doi:10.1126/science.286.5439.509

Barrera, M. (1986). Distinctions between social support concepts, measures, and models. *American Journal of Community Psychology*, *14*, 413–445.

Belgrave, F. Z., & Moorman Lewis, D. (1994). The role of social support in compliance and other health related behaviors for African Americans with chronic illnesses. *Journal of Health & Social Policy*, *5*, 55–68. doi:10.1300/J045v05n03_05

Burnkrant, R. E., & Cousineau, A. (1975). Informational and normative social influence in buyer behavior. *Journal of Consumer Research*, *2*, 206–215. doi:10.1086/208633

Cawley, J., Meyerhoefer, C., Biener, A., Hammer, M., & Wintfeld, N. (2015). Savings in medical expenditures associated with reductions in body mass index among US adults with obesity, by diabetes status. *PharmacoEconomics*, *33*, 707–722. doi:10.1007/s40273-014-0230-2

Chan, K. W., & Li, S. Y. (2010). Understanding consumer-to-consumer interactions in virtual communities: The salience of reciprocity. *Journal of Business Research*, *63*, 1033–1040. doi:10.1016/j.jbusres.2008.08.009

Clark, M. S. (1984). A distinction between two types of relationships and its implications for development. In J. C. Masters, & K. Yarkin-Levin (Eds.), *Boundary areas in social and developmental psychology* (pp. 241–270). New York, NY: Academic Press.

Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network- and small-group-based virtual communities. *International Journal of Research in Marketing*, *21*, 241–263. doi:10.1016/j.ijresmar.2003.12.004

DiMatteo, R. M. (2004). Social support and patient adherence to medical treatment: A meta-analysis. *Health Psychology*, *23*, 207–218. doi:10.1037/0278-6133.23.2.207

Elfhag, K., & Rössner, S. (2005). Who succeeds in maintaining weight loss? A conceptual review of factors associated with weight loss maintenance and weight regain. *Obesity Reviews*, *6*(1), 67–85. doi:10.1111/j.1467-789X.2005.00170.x

Eysenbach, G., Powell, J., Englesakis, M., Rizo, C., & Stern, A. (2004). Health related virtual communities and electronic support groups: Systematic review of the effects of online peer to peer interactions. *British Medical Journal*, *328*. n. p. doi:10.1136/bmj.328.7449.1166

Gibbs, J., Kim, H., & Ki, S. (2016). Investigating the role of control and support mechanisms in members' sense of virtual community. *Communication Research*. doi:10.1177/0093650216644023

Gore, S. (1981). Stress-buffering functions of social support: An appraisal and clarification of research models. In B. S. Dohrenwend, & B. P. Dohrenwend (Eds.), *Stressful life events and their contexts* (pp. 202–222). New York, NY: Prodist.

Hales, S. B., Davidson, C., & Turner-McGrievy, G. M. (2014). Varying social media post types differentially impacts engagement in a behavioral weight loss intervention. *Translational Behavioral Medicine*, *4*, 355–362. doi:10.1007/s13142-014-0274-z

Harvey-Berino, J., Pintauro, S., Buzzell, P., & Gold, E. (2004). Effect of internet support on the long-term maintenance of weight loss. *Obesity*, *12*, 320–329. doi:10.1038/oby.2004.40

Hu, L., & Bentler, P. M. (1995). Evaluating model fit. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 76–99). Thousand Oaks, CA: Sage.

Hu, Y., & Sundar, S. S. (2010). Effects of online health sources on credibility and behavioral intentions. *Communication Research*, *37*, 105–132. doi:10.1177/0093650209351512

Hwang, K. O., Ottenbacher, A. J., Green, A. P., Cannon-Diehl, M. R., Richardson, O., Bernstam, E. V., & Thomas, E. J. (2010). Social support in an Internet weight loss community. *International Journal of Medical Informatics*, *79*, 5–13. doi:10.1016/j.ijmedinf.2009.10.003

Hwang, K. O., Ottenbacher, A. J., Lucke, J. F., Etchegaray, J. M., Graham, A. L., Thomas, E. J., & Bernstam, E. V. (2011). Measuring social support for weight loss in an internet weight loss community. *Journal of Health Communication*, *16*, 198–211. doi:10.1080/10810730.2010.535106

Kim, H. (2014). Enacted social support on social media and subjective well-being. *International Journal of Communication*, *8*, 2340–2342.

Kim, H., Faw, M., & Michaelides, A. (2017). Mobile but connected: Harnessing the power of self-efficacy and group support for weight loss success through mHealth intervention. *Journal of Health Communication*. doi:10.1080/10810730.2017.1296510

Kline, R. B. (2015). *Principles and practices of structural equation modeling*. New York, NY: The Guilford Press.

Kohut, A., Keeter, S., Doherty, C., Dimock, M., & Christian, L. (2012). *Assessing the representativeness of public opinion surveys*. Washington, DC: The Pew Research Center for the People and the Press.

Lee, E. J., & Nass, C. (2002). Experimental tests of normative group influence and representation effects in computer-mediated communication. *Human Communication Research*, *28*, 349–381. doi:10.1111/j.1468-2958.2002.tb00812.x

Livhits, M., Mercado, C., Yermilov, I., Parikh, J. A., Eutson, E., Mehran, A., … Gibbons, M. M. (2011). Is social support associated with greater weight loss after bariatric surgery?: A systematic review. *Obesity Reviews*, *12*, 142–148. doi:10.1111/j.1467-789X.2010.00720.x

Nabi, R. L., Prestin, A., & So, J. (2013). Facebook friends with (health) benefits? Exploring social network site use and perceptions of social support, stress, and well-being. *Cyberpsychology, Behavior, and Social Networking*, *16*, 721–727. doi:10.1089/cyber.2012.0521

Napolitano, M. A., Hayes, S., Bennett, G., Ives, A., & Foster, G. (2013). Using Facebook and text messaging to deliver a weight loss program to college students. *Obesity*, *21*, 25–31. doi:10.1002/oby.20232

Ogden, C. L., Carroll, M. D., Fryar, C. D., & Flegal, K. M. (2015). *Prevalence of obesity among adults and youth: United States, 2011-2014* (NCHS data brief, no. 219). Hyattsville, MD: National Center for Health Statistics.

Oh, H. J., & Lee, B. (2012). The effects computer-mediated social support in online communities on patient empowerment and doctor-patient communication. *Health Communication*, *27*, 30–41. doi:10.1080/10410236.2011.567449

Rains, S. A., & Wright, K. B. (2016). Social support and computer-mediated communication: A state-of-the-art review and agenda for future research. In E. L. Cohen (Ed.), *Communication yearbook* (Vol. 40, pp. 175–211). New York, NY: Routledge.

Rains, S. A., & Young, V. (2009). A meta-analysis of research on formal computer-mediated support groups: Examining group characteristics and health outcomes. *Human Communication Research*, *35*, 309–336.

Real, K., & Rimal, R. N. (2007). Friends talk to friends about drinking: Exploring the role of peer communication in the theory of normative social behavior. *Health Communication*, *22*, 169–180. doi:10.1080/10410230701454254

Rimal, R. N., & Real, K. (2003). Understanding the influence of perceived norms on behaviors. *Communication Theory*, *13*, 184–203. doi:10.1111/j.1468-2885.2003.tb00288.x

Shen, A. X. L., Cheung, C. M. K., Lee, M. K. O., & Chen, H. (2011). How social influence affects we-intention to use instant messaging: The moderating effect of usage experience. *Information Systems Frontiers*, *13*, 157–169. doi:10.1007/s10796-009-9193-9

Sherbourne, C. D., & Stewart, A. L. (1991). The MOS social support survey. *Social Science & Medicine*, *32*, 705–714.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual Differences*, *42*, 893–898.

Stevens, V. J., Funk, K. L., Brantley, P. J., Erlinger, T. P., Myers, V. H., Champagne, C., … Hollis, J. (2008). Design and implementation of an interactive website to support long-term maintenance of weight loss. *Journal of Medical Internet Research*, *10*, e1. doi:10.2196/jmir.931

Tate, D. F., Wing, R. R., & Winett, R. A. (2001). Using Internet technology to deliver a behavioral weight loss program. *Journal of the American Medical Association*, *285*, 1172–1177. doi:10.1001/jama.285.9.1172

Turner-McGrievy, G. M., & Tate, D. F. (2013). Weight loss social support in 140 characters or less: Use of an online social network in a remotely delivered weight loss intervention. *Translational Behavioral Medicine*, *3*, 287–294. doi:10.1007/s13142-012-0183-y

Vucenik, I., & Stains, J. P. (2012). Obesity and cancer risk: Evidence, mechanisms, and recommendations. *Annals of the New York Academy of Sciences*, *1271*, 37–43.

Wright, K. B. (1999). Computer-mediated support groups: An examination of relationship among social support, perceived stress, and coping strategies. *Communication Quarterly*, *47*, 402–414. doi:10.1080/01463379909385570

Wright, K. B. (2000a). Perceptions of on-line support providers: An examination of perceived homophily, source credibility, communication and social support within on-line support groups. *Communication Quarterly*, *48*, 44–59. doi:10.1080/01463370009385579

Wright, K. B. (2000b). Social support satisfaction, on-line communication apprehension, and perceived life stress within computer-mediated support groups. *Communication Research Reports*, *17*, 139–147. doi:10.1080/08824090009388760

Wright, K. B., & Bell, S. B. (2003). Health-related support groups on the internet: Linking empirical findings to social support and computer-mediated communication. *Journal of Health Psychology*, *8*, 39–54. doi:10.1177/1359105303008001429

Wright, K. B., & Rains, S. A. (2013). Weak-tie support network preference, health-related stigma, and health outcomes in computer-mediated support groups. *Journal of Applied Communication Research*, *41*(3), 309–324. doi:10.1080/00909882.2013.792435

Zahry, N. R., Cheng, Y., & Peng, W. (2016). Content analysis of diet-related mobile apps: A self-regulation perspective. *Health Communication*, *31*, 1301–1310. doi:10.1080/10410236.2015.1072123

Zhou, T. (2011). Understanding online community user participation: A social influence perspective. *Internet Research*, *21*, 67–81. doi:10.1108/10662241111104884