Effects of Fitness Applications with SNS: How Do They Influence Physical Activity

Research-in-Progress

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Abstract

Fitness applications with social network services (SNS) have emerged for physical activity management. However, there is little understanding of the effects of these applications on users’ physical activity. Motivated thus, we develop a theoretical model based on social cognitive theory of self-regulation to explain the effects of goal setting, self-tracking, and SNS (through social comparison from browsing others’ tracking data and social support from sharing one’s own tracking data) on physical activity. The model was tested with objective data from 476 Runkeeper users. Our preliminary results show that goal setting, number of uses, the proportion of lower-performing friends, and number of likes positively influence users’ physical activities, while the proportion of higher-performing friends has a negative effect. Moreover, the effect of the proportion of higher-performing friends is moderated by the average difference between the friends and the individual. The initial contributions of the study and remaining research plan are described.

Keywords: Physical activity, fitness applications with SNS, self-regulation, social comparison, social support, Runkeeper
Introduction

Lack of physical activity is cited as a leading risk factor for mortality, and has been linked to multiple diseases such as breast and colon cancers, diabetes, and ischemic heart (World Health Organization 2013). As a result, healthcare providers and governments have been implementing initiatives to educate the public about the importance of physical activity. However, the major challenge faced by these efforts is to make people regulate themselves and perform physical activities. At the same time, technologies such as smartphones and wearable fitness devices are being integrated with fitness applications to assist users in tracking and managing their physical activities (RWJF 2014). A recent Accenture (2016) survey reported that fitness applications are the most popular among health applications, with 59% of respondents using them.

In addition to providing self-tracking features, many mobile fitness applications and websites, e.g., Runkeeper, Fitbit, Nike+, also provide social network services (SNS) to allow interactions among users. With the combination of tracking technologies and SNS, users can not only observe their own physical activities, but also share their activities with others and get informed of others’ activities. Features such as likes (for social support) and leaderboards (for social comparison) are offered for this purpose. Compared to solely using physical activity data for self-monitoring, the addition of SNS has the potential to further enhance health behaviors (Foster et al. 2010; Munson and Consolvo 2012).

However, little is known about the effects of SNS and other features of such applications on physical activity, knowledge of which can help in feature design. This is because prior research typically treated a fitness application or intervention as a whole and did not examine the separate effects of its features for goal setting, self-tracking, and SNS (Cavallo et al. 2012; Laranjo et al. 2014). Additionally, the SNS (such as Facebook groups) examined in the literature were usually not integrated with automatic tracking technologies (such as pedometers), making it challenging for users to share accurate and complete self-tracking data (Cavallo et al. 2012; Foster et al. 2010). Further, we could find only one study (Foster et al. 2010) that examined users’ sharing behavior (i.e., sharing their physical activity data with others) in fitness applications, and none accounting for their browsing behavior (i.e., browsing others’ data), which can be an important means for conveying social influence (Richardson et al. 2010).

In response to the above issues and literature gaps, we aim to examine the effect of fitness applications with SNS on users’ physical activity, and thus propose the following research question: How do the various features of fitness applications with SNS influence users’ physical activity? This study makes a preliminary attempt to address this research question by developing a theoretical model based on social cognitive theory of self-regulation to explain how different features of fitness applications with SNS influence physical activity. Social cognitive theory of self-regulation is useful here because people need to regulate themselves to overcome various impediments for conducting physical activities (Bandura 1991). Our model relates the features of fitness applications, such as for goal setting, self-tracking, social comparison (through leaderboards), and social support (through likes), to users’ number of physical activities performed. For this preliminary study, we tested the model with objective data of 476 users from the Runkeeper website. We will be further refining the model and collecting additional (including survey) data in future. The results are expected to contribute to both theory and practice in this area.

Literature Review

Through providing SNS, fitness applications and websites aim to stimulate social activities, attract and connect more users, and, importantly, motivate users to perform physical activities. While it is necessary to examine their effectiveness, prior research on technology-enabled social influence for physical activity has not investigated the impacts of various features of fitness applications with SNS. Rather, the previous literature has mainly examined the effects of interventions where the tracking tools (e.g., pedometers) and social media (e.g., forum, SNS) were separately provided (Carr et al. 2013; Cavallo et al. 2012; Foster et al. 2010; Richardson et al. 2010). For example, Foster et al. (2010) provided a pedometer for subjects to count their steps and a Facebook application for manually uploading and sharing the tracking-data. Through their experiment, they found that people using the pedometer and sharing their step count data achieved a slightly higher number of steps than those only using the pedometer. However, it is not mentioned whether the difference was statistically significant. As another example, Cavallo et al. (2012) conducted a randomized control trial where the control group only had access to a fitness education...
website. In contrast, the treatment group had pedometers for self-tracking, access to a Facebook Group for manually sharing information (e.g., updates, links and photos), in addition to access to the same fitness education website. Their analysis did not find a significant difference in the self-reported calories burned between the two groups. It should be noted that the SNS in these studies were not integrated with the self-tracking technologies (e.g., pedometers) such that users needed to manually upload their tracking data. Thus, accurate and complete tracking data may not have been shared, as opposed to automated user data collection and sharing in current fitness applications with SNS.

Additionally, Munson and Consolvo (2012) developed a mobile phone-based application for promoting physical activity, which had features for goal setting, self-tracking, and sharing the tracked data through Facebook. In the user interviews to evaluate the application, some participants said that sharing their activity data benefited them as they received support from others. However, the study did not test the effects of these features on users’ physical activities. Other than the lack of automated physical activity tracking and sharing, our review identified two other gaps in the prior literature. First, since these studies treated multiple features of the fitness applications as a whole, they did not empirically examine the effects of individual features, which is suggested as an important reason for inconsistent results about the effectiveness of SNS in achieving health outcomes (Laranjo et al. 2014). Second, only one study (Foster et al. 2010) examined the effect of users’ sharing behavior (with various limitations as mentioned above), but none accounted for their browsing behavior (i.e., browsing others’ data), which can be an important means for conveying social influence (Richardson et al. 2010). These gaps and challenges motivate us to develop and test a theoretical model to explain the effects of different features of fitness applications with SNS on users’ physical activities, where automated collection and sharing of tracking data is supported.

Theory and Hypotheses

Social Cognitive Theory of Self-Regulation

When people intend to adopt health behaviors, such as performing physical activities, they may be faced with various impediments, such as work pressure or bad weather (Bandura 1991). Therefore, self-regulation is important to manage the impediments for performing physical activities. Incorporating both inner forces and environmental influences as determinants of human behavior, social cognitive theory emphasizes the crucial role of self-regulation in the reciprocal interaction of behavior and environmental conditions (Bandura 1991). Hence it provides a comprehensive way to understand the self-regulatory process of health behavior formation. Self-regulation is defined as “self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals (p. 14)” (Zimmerman 2000). In order to understand how fitness applications with SNS could work for enhancing self-regulation and promoting physical activities, we first outline the process of self-regulation and then propose the influence of different features in this process. Figure 1 shows the phases of self-regulation, which we derived from the social cognitive theory literature (Bandura 1991; Zimmerman 2000).

![Figure 1. Phases of self-regulation derived from Bandura (1991) and Zimmerman (2000)](image)

The framework consists of three phases: forethought, performance/volitional control and self-reflection (Zimmerman 2000), where some phases have multiple components. In the forethought phase, goal setting is the focal component, which refers to the decision of pursuing certain processes and outcomes. The forethought phase is followed by the performance/volitional control phase, where self-observation of behavior takes place, i.e., a person’s self-tracking of specific aspects of his or her own performance, the conditions that surround it, and the effects that it produces (Zimmerman and Paulsen 1995). It provides
essential information for proceeding with the self-regulatory process, and plays a crucial role in the effectiveness and success of self-regulation (Baumeister and Heatherton 1996).

In the first part of the next (self-reflection) phase, i.e., self-judgment, the individual performs self-evaluation through comparing their own performance by self-observation (self-tracking) against certain standards, such as personal and social standards. As an important referential information source, social comparison, which refers to the comparison with others, could affect self-regulation through influencing the evaluation of ongoing performance (Bandura 1991; Zimmerman 2000). In our study context, social comparison is achieved through browsing others’ tracking data e.g., on a leaderboard. Leaderboards rank users according to the physical activities performed, which allows them to easily compare and evaluate their own performance against the performance of others in their social network. Based on the results of self-evaluation, people will attribute their success or failure to certain causes. Social support, which refers to the social resources available for individuals, such as information and encouragement, is suggested to influence causal attribution and help people avoid self-blame (Stewart 1989). For instance, social support could be obtained through receiving likes on one’s shared data in the context of our study.

The second part of the self-reflection phase consists of self-reaction. Self-satisfaction and adaptive or defensive inferences are two components of self-reaction. Self-satisfaction refers to whether or not individuals feel satisfied with their performance, while adaptive or defensive inferences are related to the need for changing self-regulatory strategies, such as efforts allocation and planning. Particularly, adaptive inferences are related to changes in a positive direction to augment goal-directed behavior, while defensive inferences are related to changes in a negative direction to avoid the behavior. In this phase, too, social support is helpful for building up adaptive self-regulation strategies (Anderson et al. 2006).

As per our framework, goal setting, self-tracking and social features in fitness applications with SNS have the potential to influence particular components of self-regulation and hence encourage people to perform more physical activities. The key features of fitness applications with SNS, i.e., goal setting, self-tracking, social comparison (e.g., through leaderboards) and social support (e.g., through likes), and their links to components of self-regulation will be elaborated in the following sections to formulate and justify our hypotheses. Here, the outcome of self-regulation is manifested by the number of physical activities carried out by the subject in a time period (i.e., a week), which is the dependent variable for our model.

**Goal Setting**

A goal is defined as the representation of desired processes, events, or outcomes (Austin and Vancouver 1996). It serves as an orientation function for behaviors and reflects internal standards for performance (Bandura 1991; Bandura and Wood 1989). Most previous studies examined the effects of goal setting on physical activity in the offline context (Bravata et al. 2007), where people were passively assigned certain goals (e.g., Jeffery et a. 2003). This may not have the same effect as self-set goals in fitness applications such as Runkeeper and Nike+, since goal acceptance plays an important role in determining subsequent outcomes (Locke and Latham 2002). As an exception, Munson and Consolvo (2012) developed a mobile application to promote physical activity that had a goal-setting feature in addition to other features. Their qualitative evaluation of the application suggested that users find the goal setting feature helpful.

In fitness applications with SNS, the goal setting feature allows users to specify their physical activity goals. Since goals are set by users themselves rather than assigned to them, the more relevant effect for us to study here is whether or not the use of the goal setting feature influences users’ physical activities. In this context, setting goals may influence individuals’ physical activities through two ways. First, since a goal reflects future expectancy and provides people with direction and purpose, it may generate motivations for the desired behavior through enabling people to form a clear picture about what they should do (Bandura and Wood 1989). In this sense, setting a goal in a fitness application can provide a precise target (e.g., distance and duration) and hence motivate users to increase their physical activities for goal pursuit. Moreover, since goal setting also involves people’s internal standards and provides them with a reference for performance assessment during self-regulation (Bandura and Wood 1989), using the goal setting feature to set a goal could help people make the self-judgment to achieve the goal. Thus,

*H1: Compared to those who don’t, users who set goals perform a higher number of physical activities.*
**Self-Tracking and Self-Observation**

In fitness applications with SNS, self-tracking is another integral feature used to monitor one's health behavior (Pearson 2012; VanWormer 2004). Through self-tracking (browsing one's own data), people can observe their performance of physical activities, e.g., the distance, the duration, and the calories burned. Self-tracking provides essential information for self-evaluation (Bandura 1991), which can activate self-reflection and serve as a continuous guide for actions, such as maintaining physical activities. Further, by tracking their own data, users can both share the data for obtaining social support and compare it with others' tracking data. Thus,

H2: Number of uses for self-tracking positively affects the number of physical activities.

**Social Comparison and Leaderboard**

Social comparison is the process by which people compare attributes or dimensions of themselves with others, such as academic skills, and attractiveness (Buunk and Gibbons 2007; Festinger 1954). The social comparison concept has been applied to study the effect of the leaderboards in fitness applications (Wu et al. 2015). Through leaderboards, people could easily browse others' physical activity performance and check their own rank among their social network. The underlying assumption here is that users would become more physically active in order to outperform others (Zuckerman and Gal-Oz 2014).

A few previous studies have examined the influence of leaderboards on physical activities. For example, Foster et al. (2010) developed an application, through which people can manually upload and share their step count tracked by pedometers to a Facebook application and view a global leaderboard based on step count of participants. They noted that some users said this feature could make them feel interested to exercise. However, some studies suggested that leaderboards may not work. For example, Zuckerman and Gal-Oz (2014) incorporated immediate feedback, virtual points, and a leaderboard into a mobile fitness application. Their correlation analysis indicated that access to the leaderboard based on virtual points of walking time did not increase subjects' walking time. As previously stated, the effect of individual features of these interventions was not distinguished but treated as a whole.

Depending on one's position, a leaderboard in fitness applications with SNS can offer opportunities for both upward and downward comparisons of users' physical activity performance (Wu et al. 2015). If individuals are placed high in the leaderboard (with a large proportion of lower-performing friends and a small proportion of higher-performing friends), they are more likely to identify themselves with the higher-performing friends and contrast themselves with lower-performing friends, which should lead to positive outcomes (Bailis and Chipperfield 2006) i.e., drive them to perform more physical activities. In the reverse case when people are ranked low on the leaderboard (with a large proportion of higher-performing friends and a small proportion of lower-performing friends), they are more likely to identify themselves with the lower-performing friends and contrast themselves with higher-performing friends, which should lead to negative outcomes (Bailis and Chipperfield 2006). Thus,

H3a: Proportion of higher-performing friends negatively affects the number of physical activities.

H3b: Proportion of lower-performing friends positively affects the number of physical activities.

However, the effect of the individuals’ leaderboard rank among their friends will be moderated by the difference in scores between higher-performing friends or lower-performing friends and the individual. If the difference in scores between individuals and their higher-performing friends/lower-performing friends is high, then the individual may feel that their performance is not comparable (Mussweiler et al. 2004) and become less affected by social comparison with these friends. Thus,

H4a: High average difference with higher-performing friends reduces the effect of proportion of higher-performing friends on the number of physical activities.

H4b: High average difference with lower-performing friends reduces the effect of proportion of lower-performing friends on the number of physical activities.
Social Support and Likes

Online social support refers to support received through online interaction services, such as forums, chat rooms, and SNS (Leimeister et al. 2008). It typically includes informational support and emotional support (Yan and Tan 2014). Informational support refers to advice or suggestions given for decisions or actions, while emotional support refers to love, care, sympathy, understanding, esteem or value from others. Social support is regarded as an important outcome when social media are used for promoting physical activity (Cavallo et al. 2012; Laranjo et al. 2014). For example, Cavallo et al. (2012) investigated whether providing users a pedometer for self-tracking and a Facebook Group for manually sharing information has an effect on perceived social support and physical activity. They found that both social support and physical activity level (calories burned) increased over time. However, they did not explicitly test the effect of social support on physical activity.

In fitness applications with SNS, people gain social support, such as likes, through sharing their own tracking data. In our study context, obtaining social support can influence physical activity outcomes through three ways. First, it influences people's self-judgment through affecting their causal attribution. For example, encouragement helps people avoid self-blame when encountering difficulties for performing physical activities. With social support, people will be more likely to put effort to overcome the difficulties (Bandura 1991). Second, social support is helpful for people to develop adaptive strategies, such as planning and effort allocation (Bandura 1991). Third, through showing their progress to others, people can gain recognition and affirmation for their competence (Consolvo et al. 2006). For example, in fitness applications with SNS, when people receive likes on their physical activity achievements, they will feel acknowledged and affirmed by their peers. Recognition and affirmation are suggested to be important for improving task performance (Grutterink et al. 2013). Thus,

**H5: Number of likes positively affects the number of physical activities.**

Methodology

Research Context

Our research context is the fitness community of Runkeeper, a fitness App providing self-regulatory features for physical activities, such as goal setting, self-tracking and SNS for sharing one's own tracking data or browsing others' tracking data. Runkeeper obtains users' physical activity data from smartphones and wearable devices, which could run on both iOS and Android devices. We chose Runkeeper for several reasons. First, its user base has grown to about 23 million globally since 2007 (Shontell 2013), and it scores 4.5/5 in Google Play Store with about 400,000 votes. Second, compared to other popular fitness Apps, such as Nike+ and FitBit which depend on particular sensors or wearable devices, Runkeeper has more diverse users due to its lower cost and compatibility with various tracking devices, e.g., most popular smartphones and wearables. Last, it is developer-friendly, which enabled us to collect data from it. Through the Runkeeper API and website, we collected objective data of users' and their friends' physical activities, e.g., the history of physical activities, goals, likes of each physical activity, as well as the objective data of their profile, e.g., registration date, network size, the number of total activities. The data crawling was completed in January 2016 and covered the whole of 2015. The crawling strategy was to: 1) use entries from an online English first name database as the seeds to search for users and crawl all of their data, e.g., profile and physical activity records, then 2) based on their friend list to crawl all data of their friends, as was done in previous studies (Krishnamurthy and Wills 2008).

Empirical Model

Our dependent variable, NO\_ACT\_i,t, is operationalized as the number of activities the subject performed in the current week. This was chosen because: 1) Runkeeper uses the number of activities as the indicator to construct users' leaderboard, with the leaderboard being formed from users' friend list, and 2) the number of activities is the common attribute recorded for all types of activities on Runkeeper, 3) it is an indicator

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of frequency of exercise that was used in prior studies (e.g., Kirwan et al. 2012). Table 1 shows the summary of all variables in our model.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>1. NO_ACT_{i,t}</td>
<td>Number of activities the subject i performed in week t</td>
</tr>
<tr>
<td>2. HV_GOL_{i,t}</td>
<td>Whether or not the subject i had set at least one goal, whose duration includes week t</td>
</tr>
<tr>
<td>3. NO_USE_{i,t-1}</td>
<td>Number of times the subject i used the application in week t-1 for self-tracking</td>
</tr>
<tr>
<td>4. PR_HGR_{i,t-1}</td>
<td>Proportion of total friends doing more activities than the subject i in week t-1</td>
</tr>
<tr>
<td>5. DF_HGR_{i,t-1}</td>
<td>Average absolute difference in the number of physical activities between the friends doing more activities and the subject i over week t-1</td>
</tr>
<tr>
<td>6. PR_LWR_{i,t-1}</td>
<td>Proportion of total friends doing less activities than the subject i in week t-1</td>
</tr>
<tr>
<td>7. DF_LWR_{i,t-1}</td>
<td>Average absolute difference in the number of physical activities between the friends doing less activities and the subject i over week t-1</td>
</tr>
<tr>
<td>8. NO_LKE_{i,t-1}</td>
<td>Number of likes the subject i received during week t-1</td>
</tr>
<tr>
<td>11. NT_SZE_{i,t-1}</td>
<td>Number of friends of the subject i in Runkeeper as recorded in week t-1</td>
</tr>
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</table>

The following equation represents our empirical model:

$$NO_{\text{ACT}}_{i,t} = \beta_0 + \beta_1 \cdot HV_{\text{GOL}}_{i,t} + \beta_2 \cdot NO_{\text{USE}}_{i,t-1} + \beta_3 \cdot PR_{\text{HGR}}_{i,t-1} + \beta_4 \cdot PR_{\text{LWR}}_{i,t-1} + \beta_5 \cdot PR_{\text{HGR}}_{i,t-1} \cdot DF_{\text{HGR}}_{i,t-1} + \beta_6 \cdot PR_{\text{LWR}}_{i,t-1} \cdot DF_{\text{LWR}}_{i,t-1} + \beta_7 \cdot NO_{\text{LKE}}_{i,t-1} + \text{CONTROL VARIABLE}$$

The independent variables were used with a lag except HV_GOL, which applies to the current week. The control variable included in our analysis was NT_SZE as explained below.

**Data Description**

Currently the data sample used for estimation spans 51 weeks (not including the first and last week that had incomplete data) over 2015 for 476 users. To obtain a balanced sample, the users drawn from the original crawled sample were those who registered in Runkeeper before 2015 and had done at least one activity in 2015. To obtain the interaction items, we mean centered PR_HGR, DF_HGR, PR_LWR, and DF_LWR. We computed the correlation values and VIF (table not included due to lack of space) for our model variables including the interaction terms. Since in addition to higher-performing and lower-performing friends, there also exist friends with the same performance as the subject, the correlation between PR_HGR and PR_LWR is not high (-0.12). The test for multicollinearity showed that except for DF_LWR (VIF=4.98) and PR_LWR* DF_LWR (VIF=4.46), the VIF of all variables ranged from 1.02 to 1.97 i.e., much below the threshold of 3, which indicates that multicollinearity is not an issue for the other variables (Hair et al. 2006). In order to get unbiased and consistent estimation results, we did not include DF_LWR and PR_LWR* DF_LWR in our model estimation for their high VIF and correlation (0.84), i.e. H4b was not tested.

**Preliminary Analysis and Results**

We applied a fixed effects negative binomial model (Hausman et al. 1984) on our panel data to estimate the model parameters. There are three reasons for our selection. First, our dependent variable (NO_ACT) is ordinal and hence a count data model is suitable. Second, since there are many records (~70%) in our sample with zero activities, and the dependent variable is over-dispersed, the negative binomial model is useful. Third, since the Hausman test shows a significant difference between the estimates of fixed effects vs. random effects model (p<0.001), here we estimate the fixed effects negative binomial model (see Table 2) with the Poisson model test added for robustness test. All the tested hypotheses (i.e., leaving out H4b) were found to be supported. The control variable results were as expected. Since we ran fixed effects analyses which already control for all time-invariant individual heterogeneity, typical demographic controls that are time-invariant could not be included in our analyses.
Effects of Fitness Applications with SNS

Initial Contributions and Future Plan

Although there are a number of fitness applications with SNS, e.g., Runkeeper, Nike+, there is a lack of understanding of how their features affect users’ physical activity. This study makes several initial theoretical contributions in this regard. First, we extend the literature on online health interventions and fitness applications by clarifying how goal-setting, self-tracking, and social features could affect users’ physical activity. Second, it adds to the literature using social cognitive theory of self-regulation by illustrating the effects of social comparison and social support through these applications on users’ physical activity. Third, we add to social comparison studies by identifying the effect of individual’s performance position relative to their friends on physical activities. Fourth, we contribute to the literature on social support by examining the effects of social features, such as “likes” for encouragement and affirmation. Last, this study contributes to research on goal setting through empirically testing the influence of self-set specific goals on physical activity in fitness applications with SNS.

### Table 2. Model Estimation Results for NO_ACT

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Poisson (Robust Std. Error)</th>
<th>Negative Binomial (Std. Error)</th>
<th>Hypotheses</th>
</tr>
</thead>
<tbody>
<tr>
<td>HV_GOL_{it}</td>
<td>0.37 (0.06)***</td>
<td>0.35 (0.09)***</td>
<td>H1 supported</td>
</tr>
<tr>
<td>NO_USB_{it-1}</td>
<td>0.02 (0.01)*</td>
<td>0.04 (0.01)**</td>
<td>H2 supported</td>
</tr>
<tr>
<td>PR_HGR_{it-1}</td>
<td>-0.71 (0.05)***</td>
<td>-0.60 (0.06)***</td>
<td>H3a supported</td>
</tr>
<tr>
<td>PR_LWR_{it-1}</td>
<td>0.39 (0.03)***</td>
<td>0.51 (0.04)***</td>
<td>H3b supported</td>
</tr>
<tr>
<td>PR_HGR_{it-1} * DF_HGR_{it-1}</td>
<td>-1.06 (0.07)***</td>
<td>-0.54 (0.06)***</td>
<td>H4a supported</td>
</tr>
<tr>
<td>NO_LKE_{it-1}</td>
<td>0.01 (0.003)*</td>
<td>0.01 (0.003)*</td>
<td>H5 supported</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-23447.60</td>
<td>-21123.71</td>
<td>-</td>
</tr>
<tr>
<td>Wald Test (Prob&gt;χ2)</td>
<td>0.000</td>
<td>0.000</td>
<td>-</td>
</tr>
<tr>
<td>AIC (BIC)</td>
<td>46915.20 (46995.97)</td>
<td>42269.53 (42358.28)</td>
<td>-</td>
</tr>
</tbody>
</table>

Note. Standard errors in parentheses. *p<0.05, **p<0.01, ***p<0.001, Number of Observations (users)=23800 (476)
In terms of the practical implications, by explicating how the features of fitness applications with SNS influence physical activity, this study helps developers refine the features to improve their effectiveness. First, since setting goals in fitness applications with SNS could drive people to perform more physical activities, developers may simplify the process of setting goals, e.g., by recommending goals for users to select. Second, the applications could push notifications of recent activities to users, which could remind users to use the applications. Third, the leaderboard could be adaptive to improve the placement of users with few activities. For example, designers could provide another leaderboard, in which the placement is based on users' progress rather than absolute performance if this is superior. Last, designers could make it easier to like others, e.g., press one button to like all activities of friends tracked today. Moreover, they could highlight the number of “likes” that the user received.

As a research-in-progress paper, our model and findings need further validation. First, in the next phase, we will collect subjective data through a survey to test how browsing others’ tracking data and sharing one’s own tracking data can influence the components of self-regulation, such as self-judgment and self-reaction. Second, while we used the proportion of a user's friends who outperformed and underperformed him or her on the leaderboard as objective ways to assess upward and downward social comparison, future research may test the impact of absolute leaderboard position (i.e., ranking) on physical activities. Third, as the sample is expanded and more data on goal setting is collected, we can distinguish different types of goals and assess their effects with respect to various dependent variables, such as weight loss, calories burned, and running for a certain distance. Fourth, more robustness tests will be performed to further validate our findings. For example, we could use the number of activity days for each week as the dependent variable, and then check whether there would be any differences in the model estimation. Fifth, we can include more lags for the independent variables to examine the long-term effects. Last, we intend to apply a two-stage model to investigate our research question. Specifically, the first stage will apply a selection model for users using different features, and the second stage will model for the effects of use of different features of the application on physical activities. This can add to a better understanding of health behavior change through fitness applications with SNS, which is important for individuals and society as a whole.

References


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