The Longitudinal Effects of Social Sharing on Physical Health

Completed Research Paper

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Abstract

A key strategy to combat sedentary lifestyle is to encourage fitness exercises. Traditional wellness and lifestyle management programs focus on inducing health awareness and providing fitness activity support. The growing pervasive use of smartphones allows individualized and cost-effective digital wellness programs to be administrated through mobile fitness apps. Drawing on the self-promotion literature, this paper elucidates the effects of mobile fitness app on health outcomes. Specifically, this study examines a social feature of mobile fitness app usage - social sharing. The results of our longitudinal field experiment reveal strong evidence that mobile fitness apps help improve health outcomes. Furthermore, compared the absence of social sharing, social sharing leads to lower body fatness, however the effects of social sharing diminish over time.

Keywords: Social sharing, self-promotion, field experiment

Introduction

The prevalence of obesity, which is defined as having an excessive amount of body fat, has increased dramatically in recent decades (WHO 2016). Obesity can increase one's risk for a number of chronic diseases, such as coronary heart disease, diabetes, and high blood pressure (DeFronzo and Ferrannini 1991; Huxley 2014). More alarmingly, over 100,000 Americans die each year from obesity-related deaths (CDC 2016), and the medical care of costs of obesity are staggering. In fact, the World Health Organization reported that obesity has become a worldwide epidemic. At least 2.8 million adults die each year as a result of being overweight or obese (WHO 2016).

A key strategy to combat obesity is to encourage active lifestyle, which helps regulate body fatness and improve physical fitness. Emerging research has begun exploring various app features to encourage active lifestyle. For instance, Liu et al. (2016a) noted that activity streams help show users' and friends' recent health-related activities, which could be crucial to sustaining meaningful usage engagement and outcomes. Likewise, in a study examining design principles of pervasive fitness apps, Chen and Pu (2014) found that sharing of physical activities and social interactions were important elements to motivate users to perform physical activities. Collectively, increasing evidence has highlighted the importance of social recognition to not just stimulate but also sustain interesting in

engaging fitness activities. Correspondingly, this study investigates an important app feature that facilitate social recognitions in performing fitness activities.
The issue of how technology helps transform lifestyle has been a salient topic in information systems (IS) research (e.g., Ayyagari et al. 2011; Yan and Tan 2014). However, prior research has mostly focused on adoption of health-related technologies, with less attention paid to the impacts of sustained fitness app usage. Although some recent research has explored continued usage of health-related mobile apps (e.g., van Velsen et al. 2013), our understanding beyond app usage remains largely scarce. Hence, our first objective is to study the implications of sustained mobile fitness app usage, which, surprisingly, has not attracted much attention from information systems (IS) researchers.

Emerging research has begun exploring various app features to encourage active lifestyle. For instance, Liu et al. (2016a) noted that activity streams help show users' and friends' recent health-related activities, which could be crucial to sustaining meaningful usage engagement and outcomes. Likewise, in a study examining design principles of pervasive fitness apps, Chen and Pu (2014) found that sharing of physical activities and social interactions were important elements to motivate users to perform physical activities. Collectively, increasing evidence has highlighted the importance of social recognition to not just stimulate but also sustain interesting in engaging fitness activities. Correspondingly, this study investigates the key app feature that facilitate social recognitions in performing fitness activities.

Past IS research has broadly examined the impacts of feature designs on technology usage in several contexts (e.g., Venkatesh et al. 2017). Most of these studies have revealed that when a technology is designed to be easy to use and useful to individuals, they would likely continue to use the technology at increasing usage intensity. At times, however, when individuals are distressed by certain technologies, they might opt to reduce usage, if not withdraw from further engagement altogether. More recently, IS scholars suggest that the implications of feature designs can be better understood by considering beyond immediate engagement outcomes. Embracing the importance of both immediate outcome and distal outcome of technology engagement, past research has identified two broad categories of meaningful outcomes of technology engagement, namely experiential engagement and instrumental engagement (e.g., Liu et al. 2016b). Experiential engagement is about the proximal effects of feature designs on usage intensity. Whereas useful features can motivate frequent and extensive usage, inept features might inhibit comprehensive adoption. Instrumental engagement is about the distal outcomes of technology usage. For instance, high mobile fitness app usage might help reduce healthcare expenditures and maintain weight loss. Correspondingly, the second objective of this study is to elucidate the specific experiential and instrumental engagement of mobile fitness apps.

To achieve the research objectives, we identify a key design feature of mobile fitness app that facilitates social recognition and investigate the effects of the design feature on experimental engagement, which in turn influence instrumental engagement outcomes. We tested the proposed model using a longitudinal field experiment. By developing and validating the model, this research contributes to both research and practice in this area.

Theoretical Foundation

In this section, we introduce the theoretical basis upon which our research model is built. First, we introduce the self-promotion literature, which helps understand the role of information dissemination on augmenting individuals' status and attractiveness on online social networks. Second, past research examining technology usage is discussed. Finally, we review the sports science literature to provide some understanding on the physical impacts of performing fitness activities.

Self-Promotion

Self-promotion is the process by which individuals attempt to influence the images that others have of them (Rosenfeld et al. 1995). Designed to augment one's status and attractiveness, self-promtion includes pointing with pride to one's accomplishments, speaking direlty about one's strengths and telents, and making internal rather than external attributions for achievements. Self-promotion has been studied in a wide variety of contexts, such as interviwewing, performance appraisal, feedback seeking, and social interactions. The general goal of self-promotion is to create a particaulr impression in others' minds (Leary and Kowalski 1990).

The self-promotion literature has substantiated the importance of disclosure regulation, through which indivduals tailor the disclosure about themsevles in such a way that it best serves their self-promotions. For example, Liu et al. (2016b) found that online self-promotion was often achieved through sharing information about individuals' daily experiences on social media. Likewise, Shang et al. (2017) revealed that individuals could enhance their social status through expressing their ideas and communicating opinions on their online social networks.

This study uses social sharing to charazterize the key self-promotion design in mobile fitness apps. Social sharing is an information dissemination mechanism that facilitates the publication of fitness activities to users' online social networks (Consolvo et al. 2006). The presence of social sharing enables users' performance in fitness activities to be made known to their online friends. By contrast, the absence of social sharing keeps users' fitness activity private, and hence unlikely to contribute to identity maintenance and peer awareness.

The Duality of Self-Promotion

While self-promotion is often used to generate desired images, Jones and Pittman (1982) caution that attempts at self-promotion invariably carry the risk of being perceived negatively; that is, for every promotion about self, there is a corresponding undesired image that is risked. For example, an individual engaigng in self-promotion hopes to come across as competent; however, he or she risks coming across as conceited instead. Indeed, in a longtidual study examing of personal perceptions in discussion groups, Paulhus (1998) found that group members largely maintained positive impressions towards self-promotoers in the initial periods, whereas their positive impressions deteroiated to negative perceptions over time.

Increasing evidence suggests that self-promotion is not entirely an automonous actvity. Rather, self-promotion is an interpersonal process that involves careful monitoring about the social environment and making adjustment to self-promotions. Self-promotion is about conveying desired identities in social environment whereby individuals present identity-relevant information to some interactants and carefully evaluate the responses of interactants (Human et al. 2012). Oftentimes, based on the responses, individuals might have to tailor their self-promotions to suit different social situations (Snyder and Gangestad 1982).

Experimental Engagement Outcomes: Usage Intensity

Past IS research has substantially broadened understanding of technology usage. Burton-Jones and Straub (2006) suggest that technology usage is not a monolithic construct but is a complex activity. Specifically, technology usage can be conceptualized in two aspects, namely lean usage and rich usage. Whereas lean usage typically focuses on duration of technology usage, rich usage represents the extent to which features in the system that relate to the core aspects of the tasks are used. Lean usage captures the entire content of the usage activity in an omnibus measure such as use/nonuse or duration of use. Although lean usage is mostly convenient to operationalize, it is insufficient to fully reflect the most relevant aspect of usage in a specific context, such as mobile fitness app usage. Rich usage, in contrast, goes beyond capturing the extent to which the technology is used by incorporating the user or task context in the conceptualization. For instance, in the context of mobile fitness app usage, rich usage can be realized through the jogging distance that is tracked when users perform jogging activities with the app.

This study draws upon the work of Burton-Jones and Straub (2006) to provide contextualized understanding of two aspects of mobile fitness app usage. To reflect the lean aspect of mobile fitness app usage, this study focuses usage persistence, which refers to the frequency of mobile fitness app usage. A low usage persistence represents sporadic performance of fitness activities, whereas a high usage persistence denotes frequent performance of fitness activities. The sports science literature has vastly supported the importance of persistent engagement of fitness activities. The uptake of persistent fitness activities is typically associated with improving muscle-fat ratio, bone strength, and flexibility while minimizing the likelihood of exhaustion and injuries.

The rich aspect of technology usage concerns usage of technology that is pertinent to the context of usage (Burton-Jones and Straub, 2006). Accordingly, this study focuses on usage endurance, which subsumes the average distance tracked in using mobile fitness apps. While a low usage endurance is indicative of the performance of short running episodes, a high usage endurance implies performance of long-distance running activities. With low usage endurance, users are unlikely to maintain high heart-rate in fitness activities, which is essential to improving cardiovascular fitness and aerobic power. High usage endurance, in contrast, suggests that users are likely to have maintained high heart-rate for a substantial period during fitness activities.

Instrumental Engagement Outcomes: Physical Health

Evidence suggests that when repeated usage of technology might contribute to a wide spectrum of fundamental transformation. Past IS research has broadly demonstrated the transformational impact of prolonged technology usage on individuals and organizations. For example, Krasnova et al. (2015) examined usage of online social networking websites and found that prolonged consumption of social information would intensify the experience of envy, which could evoke prolonged damage to users' cognitive well-being and affective well-being. Similarly, Ayyagari et al. (2011) examined techno-stress and revealed that technology could make individuals overly reachable and hence creating an enormous amount of technology-driven stress, such as work-life conflicts and work overload. More important, when employees were made to use the technology over a prolonged period, technology-driven stress could create long-lasting psychological strain, such as exhaustion, burnt-out, and mental fatigue.

This study draws upon the sports science literature to provide a better understanding of the specific physiological impact of sustained mobile fitness app usage. According to the literature, frequent physical exercises could help manage fatness (Cress et al. 1996). Fatness is typically associated with physiological health, which is the basic cellular and anatomic function such as cardiac ejection fraction, nerve conduction velocity, or muscle strength. Reflecting the importance of fatness, this study examines *body-mass index* (BMI), which is defined as the weight in kilograms divided by the square of the height in meters. It is an index of weight-for-height that is commonly used to classify underweight, overweight, and obesity in adults. Ample evidence suggests that increasing BMI are closely related to health risks. For example, in a meta-analysis involving 282,137 patients, Renehan et al. (2008) found that increase in BMI was strongly associated with oesophageal adenocarcinoma and with thyroid, colon, and renal caners.

Research Model and Hypotheses Development

The research model is presented in Figure 1. Specifically, we hypothesize the effects of social sharing on mobile fitness app usage intensity. We also propose investigating the moderating role of usage tenure on the relationship between social sharing and usage intensity. Lastly, we explore the impact of mobile fitness app usage intensity on physical health.

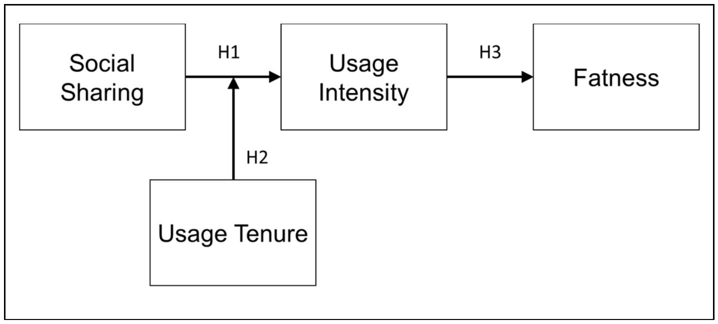

Figure 1. Research Model

Prior research on self-promotion in the technology usage context found that information dissemination has a positive influence on users' intention to adopt technology (Beck et al. 2014; Carter 2015) and users will form positive perceptions about continuing to explore the technology. Self-promotion through autonomous information dissemination made by the technology was found to be more image-enhancing than disclosure made by users. As a stimulus, the social sharing feature vividly promotes users' active lifestyle by showcasing the performance of their fitness activities, which can often be a novel form of content about users. For example, if a user completes a running activity with the social sharing feature, the distance and time that he or she has spent exercising will be made available to Facebook friends. This social dissemination function is expected to become a novel mechanism to promote users' active lifestyle, which helps enhance their healthy identity and hence encourage high usage intensity in the initial phrases of usage

The effects of social sharing on usage intensity can be explained by the self-determination theory, which posits that when activities are not inherently interesting or enjoyable, a key reason for individuals to persist is often the fulfillment of need for relatedness during the activities. Need for relatedness reflects the need to experience a sense of belonging, attachment, and intimacy with others (Deci and Ryan 2000). It subsumes the desire to be emotionally connected to and interpersonally involved in warm, caring, and responsive relationships (Niemiec et al. 2006). Fitness activities could at times be monotonous and repetitive (e.g., long distance jogging). the satisfaction of relatedness needs is a key mechanism to overcome boredom in sustained fitness activities. Indeed, in a study examining behavioral weight control treatment, Jelalian et al. (2010) found that peer involvement in exercise activities was important to sustaining physical exercises for weight management. Similarly, Duncan and McAuley (1993) found that the provision of social relationships, such as interpersonal connectivity, relational attachment, and social integration, helped bolster motivation to adherent to exercise regime. In a longitudinal study, Curran et al. (2016) found that satisfaction of relatedness needs was a key determinant of sports activity engagement. Similarly, Standage et al. (2003) examined the contextual motivation in physical educations and found that the sense of relatedness developed in compulsory physical training enhanced individuals' willingness to partake additional fitness activities in leisure time.

Although social companion in fitness activities might mitigate exercise boredom, it could be challenging, if not impossible, to maintain regular companionship. In using mobile apps, the fulfillment of relatedness needs is an important feature, which helps entice sustained usage. While mobile apps might have implemented a myriad of features to facilitate relatedness experience, mobile fitness apps typically implement two types of social connectivity features, namely post-event social participation and real-time social participation. Whereas post-event social participation focuses on providing relatedness support as a resource or outcome, real-time social participation focuses on facilitating relatedness support as a process. When social fitness apps are used with post-event social participation, at the completion of the exercise episodes, users would be able to disseminate their fitness activities to their online social networks. The dissemination of fitness activities often incites online social interactions, which allows users to garner informational support and emotional support. Informational support can be obtained through informative comments provided by users' online friends. For instance, by sharing the route of a jogging episode, users might receive recommendations on other jogging routes and invitations to jogging events, which help emphasize their sense of relatedness in using the mobile fitness app. Emotional support often comes in the form of expressing support and caring in comments and social reactions. This kind of support is especially important for users who are not used to persisting strenuous fitness activities. For example, users who are not ready for strenuous fitness activities can become physically strained and hence disengaging from exercising over time. Emotional support from peers sends a signal to users that users' perseverance is recognized and provides encouragement to them to continue with engaging fitness activities.

Further, research indicated that users will enjoy taking up fitness activities that provides some immediate gratifications in short terms (Woolley and Fishbach 2016). For example, social gratifications created by making users' achievement in playing mobile app games to friends were found to have a positive impact on users' pleasure with initial app usage (Wei and Lu 2014). Similarly, social gratifications resulting from publicizing users' fitness activities have been shown to influence users' enjoyment in adopting mobile fitness apps (Vaterlaus et al. 2015). Thus, in the early phrases, a mobile fitness app that incorporates a social sharing feature is expected to lead to greater usage intensity compared with a mobile fitness app lacking such a feature.

H1: In the early phrases, compared with the absence of social sharing, the presence of social sharing will lead to lower usage intensity of mobile fitness apps.

The above section hypothesized the novel effects of social sharing and asserted that the presence of social sharing leads to higher usage intensity in initial phrases. However, some emerging evidence suggests that the way self-promotion is facilitated through social sharing might not be entirely consistent over time. Colvin et al. (1995) found that time was a critical moderating factor between self-promotions and perceptions about individuals. Specifically, the authors revealed that self-promotors might enjoy initial social attentions and hence enhancing their status among friends. However, repetitive self-promotions could eventually offend others. After the positive perceptions to self-promotions wore off, friends might gradually have developed impressions of narcissism. Over time, individuals who perform repetitive self-promotions can be viewed as arrogant, hostile, and defensive (Morf and Rhodewalt 1993).

Repetitive self-promotion is considered one of the key determinant factors of annoyance (Scopelliti et al. 2015). Godfrey et al. (1986) suggested that the relationship between repetitive self-promotion and interaction intensity is likely curvilinear. Repetitive self-promotion may initially be novel to online social networks and hence helps reinforce the identities of users. However, beyond a certain level of repetitive self-promotion, the novelty of self-promotion is likely to reduce, creating a condition of "information redundancy" that leads to irritating and annoying online friends. Lee et al. (2012) found that users were often initially attracted by the self-presentation in promoting in-app achievement to social networks to explore app games. However, after some time, users were typically found to be concerned about the repetitive self-promotion messages that could be irritating to their online friends. Likewise, we expect that as mobile fitness apps with social sharing is used over time, users will not only experience diminishing self-promotions but also become concerned about irritating their online social networks. Consequently, their usage intensity is likely to follow an inverted U-shaped curve. Thus, we propose the following:

H2: Over time, usage Intensity with the presence of social sharing will follow an inverted U-shaped curve as the level of usage tenure increases.

Ample research has demonstrated the effects of regular and substantive exercise training on weight. Individuals who take on fitness exercises are usually thin and of lower body fat compared with sedentary others. In general, the medical literature has revealed that there is a consistent negative relationship between level of activity and body mass index (Bouchard et al. 1993). For instance, in a study examining exercise-induced weight loss, Ross et al. (2000) instructed subjects to perform daily exercise (i.e., brisk walking or light jogging) on a motorized treadmill for 12 weeks and reported that subjects had lost about 8% of initial body weight. More important, compared with diet-control, regular exercise led to more total fat reduction and less skeletal muscle mass decrease, which was vital to maintaining metabolism that protected against insulin resistance and obesity.

Past research examining weight management has prescribed a variety of interventions to improve BMI. Despite the diversity of interventions, the key underlying principle of weight management is to sustain an energy deficit, which is about maintaining a shortfall between energy intake and energy needs of the body. A key technique of inducing an energy deficit is to increase energy expenditure through increase in physical activity, which can be progressively increased in terms of exercise duration and exercise frequency. Exercise duration refers to the time period that individuals engaged fitness exercises. The typical public health recommendation is for individuals to participate in a minimum of 150 minutes of physical activity per week. Emerging evidence suggests that levels of exercise greater than this minimum recommended amount may be important for maintaining weight loss long-term. In particular, Jakicic et al. (1999) examined the effects of exercise duration on weight loss and found that individuals gradually increased their exercise duration to approximately 280 minutes per week showed no weight regain after an 18-month weight loss program, whereas individuals exercising less than 200 minutes per week showed significant weight regain after 6 months. Similarly, in using mobile fitness apps, since usage duration implies exercise duration, users who maintain higher usage duration over time will have greater improvement in BMI.

Exercise frequency refers to the regularity that individuals engaged fitness exercises. The general health recommendation is for individuals to perform some form of fitness activities in most, preferably all, days of the week (Pate et al. 1995). Ample evidence has demonstrated the importance of frequent fitness exercise in regulating weight. For example, Borg et al. (2002) examined weight loss maintenance in obese and found that individuals who gradually increased their exercise duration to a weekly total energy expenditure of 10.1 mega-joules helped maintain weight loss after completing a weight maintenance program. However, individuals who were unable to accomplish the gradual increase in exercise duration reported weight regain. Likewise, in using mobile fitness apps, since usage frequency represents exercise frequency, users who have maintained higher usage frequency over time will have greater improvement in BMI. In sum, we posit the follows:

H3: Change in usage intensity will be negatively related to change in BMI over time.

Research Methodology

Participants and Experimental Procedure

A longitudinal field experiment was conducted to investigate the research model. 213 subjects completed the study, which lasted for 6 months. The average age of the subjects was around 31 years old. Usage intensity was recorded by observing subjects' app usage log (i.e., usage duration and tracked distance) every month. Fatness was captured every 2 months. Subjects were randomly allocated to one of the experimental conditions. A training session to familiarize subjects with the mobile fitness app. Subjects' weights and heights were captured. They were encouraged to use the app to keep track of their fitness exercises.

Social sharing was manipulated by enabling (disabling) the social media posting feature in the mobile fitness app. When the feature was enabled, the app would disseminate tracked activities through subjects' social media accounts. In contrast, when the feature was disabled, tracked activities were not published by the app on behalf of the subjects. Subjects were instructed to enable (disable) social sharing during the training session, where they were given a manual that contained instructions to enable (disable) several features, in addition to social sharing.

Usage intensity was captured in two aspects, namely usage persistence and usage endurance. Usage persistence was measured using the amount of usage episodes in each one-month period. Usage endurance was measured using the usage time of the mobile fitness app in each one-month period. Body-mass index was capturing by measuring subjects' weight and height.

Data Analysis

The Effects of Social Sharing on Usage Intensity

This study centered on the effect of social sharing on usage intensity over time. Accordingly, we performed a repeated-measures ANOVA on the usage intensity data with social sharing as predictor. The entire 6-month period was considered in six stages (each stage covers a 1-month period). This allowed us to identify (1) the overall effect of social sharing, and (2) the specific stage that social sharing had differential effects on usage intensity. Accordingly, for each stage that displayed a main effect or an interaction, we extracted mean parameter estimates to perform follow-up repeated-measures analyses, such as examining the direction and strength of any linear trends with repeated presentations.

Repeated measures of analysis of variance (RM-ANOVA) were conducted to evaluate the longitudinal differences between the two experimental groups. We considered the initial 2-month period as the early stage, where subjects were expected to focus on adopting and exploring the mobile fitness app, in testing H1. Accordingly, the resulting design is a 2 (social sharing absence vs. presence) by 2 (time periods). Social sharing served as a between-groups factor while the others were within-subject or repeated measures factors.

RM-ANOVA with usage persistence as the dependent variable was performed. Results suggest that the presence of social sharing leads to a significantly higher usage persistence than the absence of social sharing ($F(1, 237) = 2318.77$, $p<.001$) (Table 1). Similarly, RM-ANOVA with usage endurance as the dependent variable was performed. Results suggest that the presence of social sharing leads to a significantly higher usage endurance than the absence of social sharing ($F(1, 237) = 14182.44$, $p<.001$) (Table 1). Therefore, H1 is supported.

Table 1: Tests of Within-Subjects Contrasts

Source	*Type III Sum of Square*	*df*	*Mean Square*	*F*	*Sig.*
Between-Subjects Effects					
Intercept	170231.55	1	170231.55	32212.71	.000
SS	2318.77	1	2318.77	1021.21	.000
Error	1216.51	237	3.85		
Within-Subjects Contrasts					
Stages	2453.11	1	2453.11	1127.21	.000
Stages * SS	221.30	1	221.30	65.22	.000
Error(Stage)	1123.22	237	2.91		
DV = Usage Persistence					
Source	*Type III Sum of Square*	*df*	*Mean Square*	*F*	*Sig.*
Between-Subjects Effects					
Intercept	120274.02	1	120274.02	4227.64	.000
SS	14182.44	1	14182.44	37.54	.000
Error	21466.58	237	2133.12		
Within-Subjects Contrasts					
Stages	142873.18	1	142873.18	1156.20	.000
Stages * SS	4386.60	1	4386.60	28.68	.000
Error(Stage)	37463.40	237	152.98		
DV = Usage Endurance					

The Interaction Effects of Social Sharing and Usage Tenure on Usage Intensity

Repeated measures of analysis of variance (RM-ANOVA) were conducted to evaluate the longitudinal differences between the two experimental groups. The resulting design is a 2 (social sharing absence vs. presence) by 6 (time periods). Social sharing served as a between-groups factor while the others were within-subject or repeated measures factors.

RM-ANOVA with usage persistence as the dependent variable was performed. Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated, χ^2 (14) = 297.12, p<.001, and therefore, a Greenhouse-Geisser correlation was used. Results suggest that the presence of social sharing leads to a significantly lower usage persistence than the absence of social sharing (F(1, 237) = 5070.08, p<.001) (Table 2). Results in Table 11 also showed that stages have a significant effect on usage persistence (F(3.87, 1705.52) = 18790.63, p<.001). The interaction effect of stages and social sharing had a significant effect on usage persistence (F(3.87, 1705.52) = 2260.27, p<.001).

Table 2: Tests of Within-Subjects Contrasts

Source	Type III Sum of Square	df	Mean Square	F	Sig.
Between-Subjects Effects					
Intercept	1141867.61	1	1141867.61	118190.06	.000
SS	5070.08	1	5070.08	524.78	.000
Error	4260.63	237	9.66		
Within-Subjects Contrasts					
Stages	18790.63	5	3758.13	18790.63	.000
Stages * SS	39632.97	5	7926.59	2260.27	.000
Error(Stage)	7732.78	237	3.51		

Notes: DV = Usage Persistence

Similarly, RM-ANOVA with usage endurance as the dependent variable was performed. Mauchly's Test of Sphericity indicated that the assumption of sphericity had been violated, χ^2 (14) = 2442.83, p<.001, and therefore, a Greenhouse-Geisser correlation was used. Results suggest that the presence of social sharing leads to a significantly lower usage endurance than the absence of social sharing (F(1,441) = 146.11, p<.001) (Table 3). Results also showed that stages have a significant effect on usage endurance (F(1.41, 623.56) = 155.18, p<.001). The interaction effect of stages and social sharing had a significant effect on usage endurance (F(1.41, 623.56) = 554.78, p<.001). Therefore, H2 is supported.

Table 3: Tests of Within-Subjects Contrasts

Source	Type III Sum of Square	df	Mean Square	F	Sig.
Between-Subjects Effects					
Intercept	81217456.21	1	81217456.21	16294.41	.000
SS	728255.46	1	728255.46	146.11	.000
Error	2198108.98	237	4984.37		
Within-Subjects Contrasts					
Stages	906270.21	5	181254.04	155.18	.000
Stages * SS	3240050.96	5	648010.19	554.78	.000
Error(Stage)	2575529.59	237	1168.04		

Notes: DV = Usage Endurance

The Physical Impact of Mobile Fitness App Usage

Given that understanding the impact of usage intensity on fatness and fitness over time is the focus of the right-hand side of the research model, we needed a data analytic approach that would allow us to evaluate the longitudinal effects. Recent research suggests that latent growth modeling (LGM) is a powerful and integrative approach to assess change in research variables (e.g., Bala and Venkatesh

2013). LGM helps measure change in variables over time, and more importantly, validates causal models to predict the change and assess the effect of change on outcome variables within a single structural model (e.g., Jokisaari and Nurmi 2009; Zheng et al. 2014).

Following past research adapted the LGM approach (e.g.,Bentein et al. 2005), this study employed a two-step approach to conduct the LGM analysis. In the first step of the analysis, we set to find out the nature and magnitude of change in usage intensity (usage persistence and usage endurance), fatness, and fitness. We tested three different models, namely a no-growth model, a linear growth model, and a quadratic growth model, to determine the functional form of change (e.g., whether there were increasing or decreasing trajectories of changes) in the research variables. Consistent with prior research employing LGM, we included the residual covariance between consecutive indicators of the same variable (e.g., fatness at Time 1, Time 2, and Time 3). In the second step, we constructed a dual growth LGM with usage intensity as predictors and fatness as well as fitness as distal outcomes. To ensure interpretability of results, usage persistence and usage endurance were computed on a 2-monthly basis, which is consistent with the measurement frequency of fatness (i.e., fatness was measured every 2 months). Table 4 presents a summary of our key constructs and how they were used in the LGM analysis.

Table 4. Operationalization and Use of Constructs in LGM Analysis

Construct	Measurement Occasion	Use in LGM Analysis
Usage persistence	T_1: amount of usage frequency 2 months after commencement of experiment T_2: amount of usage frequency in next 2 months (3rd and 4th month) T_3: amount of usage frequency in final 2 months	Changes in usage persistence were assessed as a difference among subjects' mobile fitness app usage frequency in T_1, T_2, and T_3. In LGM analysis, the measure of the same construct at three (or more) different time periods allows the estimation of the trajectory of change over time, such as no change, linear change, or complex change (e.g., nonlinear and quadratic changes).
Usage endurance	T_1: amount of usage duration 2 months after commencement of experiment T_2: amount of usage duration in next 2 months (3rd and 4th month) T_3: amount of usage duration in final 2 months	Changes in usage endurance were assessed as a difference among subjects' mobile fitness app usage duration in T_1, T_2, and T_3. In LGM analysis, the measure of the same construct at three (or more) different time periods allows the estimation of the trajectory of change over time, such as no change, linear change, or complex change (e.g., nonlinear and quadratic changes).
Fatness	T_1: 2 months after commencement of experiment T_2: 4 months after commencement of experiment T_3: 6 months after commencement of experiment	Changes in fatness were assessed as a difference among subjects' body mass index at T_1, T_2, and T_3. In LGM analysis, the measure of the same construct at three (or more) different time periods allows the estimation of the trajectory of change over time, such as no change, linear change, or complex change (e.g., nonlinear and quadratic changes).
Baseline measures	T_0: immediately after	The T_0 measure was used as an

• Age • Body Mass Index • Previous fitness test results • Reported physical activeness • Amount of Facebook friends	commencement of experiment	exogenous control variable to partial out the effects of age, past body mass index, reported physical activeness, and amount of Facebook friends.

Table 5 provides important information regarding the nature of changes across the four variables. As shown in the table, the mean initial status of usage persistence was 60.82 and usage endurance was 176.34. These were the levels of usage persistence and usage endurance subjects had in the initial phase (i.e., Time 1). The variance of initial status for both usage persistence and usage endurance were statistically significant (16.50, p<.001 for usage persistence and 1537.77, p<.001), suggesting that systematic individual difference in usage persistence and usage effort in the initial phase such that some individuals had higher levels of usage persistence and usage endurance than others. Further, the change variance in both variables (i.e., usage persistence and usage endurance) were statistically significant (47.32, p<.001 for usage persistence and 1610.08, p<.001), indicating that some individuals demonstrated a greater increase in usage persistence and increase in usage endurance. The negative and significant initial status and change covariance (-26.83, p<.001) for usage persistence and (-896.98, p<.001) for usage endurance indicated that the initial status of usage persistence and usage endurance was negatively associated with its increase, suggesting that individuals who had lower levels of initial usage persistence and usage endurance experienced a greater increase in usage persistence and usage endurance than those who had a lower mean level of usage persistence and usage endurance at T1.

Table 5. Growth Parameter Estimates (Optimal Growth Model)

Variables	Initial Status (IS)		Change (CH)		Covariance
	Mean	Variance	Mean	Variance	(IS-CH)
UP	60.82***	16.50***	4.54***	47.32***	-26.83***
UE	176.34***	1537.77***	10.24***	1610.08***	-896.98***
Fatness	21.67***	1.36***	-0.37***	-0.46***	0.27***

NOTE: *p<0.05, **p<0.02, ***p<0.001.

The mean initial status of fatness was 21.67. This was the level of fatness individuals had in the initial phase (i.e., Time 1). The variance of initial status for fatness (1.36, p<.001) was significant, suggesting that systematic individual difference in fatness in the initial phase such that some individuals had higher levels of fatness than others. Further, the change variance in fatness was statistically significant (-0.46, p<.001 for fatness), indicating that some individuals demonstrated a greater decrease in fatness. The positive and significant initial status and change covariance (0.27, p<.001) for fatness indicated that initial status of fatness was positively associated with its decline.

We created a dual-growth structural model incorporating predictors and outcomes of changes in fatness to test our model (i.e., H3). This model yielded a good fit to the data: $\alpha^2 = 103.48$, p<.001 CFI = .99, NNFI = .98, RMSEA = .03, SRMR = .05. As Table 6 shows, the intercept of usage persistence has a significant negative effect on the slope of fatness (β = -0.20, p<.001). This implies that at the onset of the measurement period (i.e., T1), individuals with stronger usage persistence at T1 have greater decrease in fatness over time. Furthermore, the slope of usage persistence has a significant negative effect on the slope of fatness (β = -0.07, p<.001), which suggests that higher usage persistence over time leads to lower fatness. Similarly, the intercept of usage endurance has a significant negative effect on the slope of fatness (β = -0.09, p<.001) and the slope of usage endurance has a significant negative effect on the slope of fatness (β = -0.01, p<.001). These results suggest that higher initial level of usage endurance and a higher usage endurance over time lead to lower fatness. Collectively, higher usage persistence and higher usage endurance over time are found to lead to lower fatness. Therefore, H3 is supported.

Table 6. Coefficients of the Dual Growth LGM

	Effects on Intercept of Fatness	Effects on Slope of Fatness
Intercept of UP	-0.32*** (0.06)	-0.20*** (0.04)
Slope of UP	-0.16*** (0.03)	-0.07*** (0.02)
Intercept of UE	0.01*** (0.04)	-0.09*** (0.00)
Slope of UE	-0.01* (0.04)	-0.01*** (0.03)

Discussion

Self-promotion is a key premise underlying many technologies designed to promote active lifestyle (e.g., bragging about fitness improvement), and for theories describing such processes as self-presentation, social gratifications, and bragging, which posit that individuals often monitor the responses of others to regulate their self-promotion activities. The insinuation is that this regulation of self-promotion activities has implications on the impacts of social sharing over time. Despite the previous research attempts to do so, the fact is that this fundamental premise underlying self-promotion regulation remains relatively unexamined. The purpose of this study was to test whether the effects of social sharing on usage intensity significantly change across time and, if so, to address whether these changes are meaningful to our understanding of health outcomes induced by fitness app usage. This study shows that social sharing powerfully drives usage intensity (i.e., usage persistence and usage endurance) in early phrase but inhibits intensive usage in the long term. Additionally, we demonstrate that increase in usage intensity is helpful in reducing fatness.

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