Gamification in Fitness Apps: How do Leaderboards influence Exercise?

Research-in-Progress

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Abstract

While leaderboards are a key gamification element incorporated in fitness apps to spur competition among users, various issues exist in their use. Yet, the impact of leaderboards and the social comparison they entail in these apps is under-studied and not well understood. Motivated thus, we build a theoretical model to explain their impact on the attitude and physical activity behavior of users by drawing on social comparison theory. We also propose that environmental (perceived competitive climate) and individual (self-efficacy) factors moderate the relationship between social comparison via leaderboards and users attitude. The model was tested by collecting survey and objective website data from 80 users of Nike+ Running. Our results show that users’ attitude and facilitating conditions increase their physical activity behavior. Additionally, perceived competitive climate and self-efficacy moderate the effect of social comparison on users’ attitude in opposing directions. The expected contributions and remaining research plan are described.

Keywords: Gamification, leaderboard, fitness app, physical activity behavior, attitude, social comparison.
Gamification in Fitness Apps

Introduction

While its precursors such as loyalty programs have existed for years (Sharp and Sharp 1997), the term “gamification” gained popularity around 2010, marking the emergence of this industry. Since then, over 70% of Global 2000 companies have implemented at least one gamified application (Hollander 2014). With the growing demand from organizations, the global gamification market is expected to reach $5.5 billion by 2018 (MarketsandMarkets 2013). Indeed gamification, defined as using game elements and techniques in non-game contexts (Deterding et al. 2011), is being widely applied in different industries (Kankanhalli et al. 2012). For instance, in the healthcare domain, fitness applications installed on smartphones aim to take advantage of gamification design to achieve better health outcomes.

Previous research has observed that the main reason why games are fun is that they provide fantasies, evoke curiosity, and create challenges for players (Malone 1980). Thus, a key function of a game is to create challenges, which can be facilitated by comparison and competition among players (Schiesel 2005; Totty 2005). When incorporating this idea into gamification design, leaderboards are regarded as an important element to drive such effects among users (Thiebes et al. 2014). They highlight comparisons and stimulate competition in gamified systems by showing users where they rank relative to their peers. This allows direct and immediate comparisons, compared to other gamification elements such as levels and badges.

Our focus in this study is on the use of leaderboards in fitness apps such as Nike+ Running and RunKeeper since this category of apps are the most widely used (RWJF 2014) and aim to encourage a healthy lifestyle in order to reduce the risk of chronic diseases (WHO 2015). However, though leaderboards are widely incorporated in fitness apps, various issues still exist in their use. Particularly, app developers have to find ways to motivate every user, not just the top performers, and need to keep users in different positions engaged even if they have fallen behind (Hollander 2014). To address such issues, it is necessary to explore the underlying mechanisms through which leaderboards work in influencing individuals’ physical exercise behavior recorded in fitness apps.

However, most prior studies on leaderboards have been conducted in the learning and education context, and inconsistent outcomes have been reported. While several studies reported that the learning outcomes from using leaderboards were mostly positive by increasing motivation, engagement, and enjoyment regarding the learning task, e.g., Halan et al. (2010), Cheong et al. (2013), other studies have observed negative outcomes, e.g., De Schutter and Abeele (2014), Hanus and Fox (2015). The mixed findings could be due to contingencies or conditions that have not been accounted for before. As per the prior literature, we know little about how leaderboards affect individuals’ psychological and behavioral responses, especially in the health and fitness context. Thus, the issues faced by fitness app developers along with the lack of existing research and understanding of this topic motivate our study.

Accordingly, our research question for this study is: How does social comparison through leaderboards in fitness apps impact individual’s attitude and physical exercise behavior and under what conditions? We address this question by building a theoretical model drawing on social comparison theory (Festinger 1954). Social comparison theory is useful here because leaderboards are aimed at motivating desired behaviors by allowing individuals to directly compare their own performance with others (Bunchball 2010). We have carried out a preliminary study of 80 Nike+ Running users using both subjective (survey) and objective website data to test our model and are in the process of collecting additional data. The results are expected to contribute to both theory and practice in this area.

Conceptual Background

**Fitness Apps, Gamification, and Leaderboards**

The popularity of smartphones has driven the shift to using mobile computing and apps for managing chronic diseases and health maintenance (Klasnja and Pratt 2012). Indeed, the two major smartphone platforms, Apple and Android app store, have seen a tremendous growth of mHealth apps, reaching more than 100,000 apps in the first quarter of 2014. Among these, fitness apps constitute the largest category i.e., 30.9% (Research2guidance 2014). Unsurprisingly, the majority of users of fitness apps are...
young adults and students (Price 2014). Leveraging on the prominent role of games in the culture of young people (Dorman 1997), today’s fitness apps aim to apply gamification elements as an incentive for user engagement and adherence (McCallum 2012). For fitness app developers, understanding the effects of gamification elements and applying them appropriately has become increasingly necessary.

In the related literature, though not through leaderboards, researchers have examined the influence of peers on individuals' effective health management. For instance, Hamari and Koivisto (2013) found that social factors were predictors for the continued use of a physical exercise app and the intention to recommend the app to others. Similarly, a study examining a social computer game for physical activity found that the application of game elements could create initial excitement, increase participants' awareness, and motivate an increase in the activity level in a fun and engaging way (Lin et al. 2006). However, opposing effects have also been reported. For example, Consolvo et al. (2006) noted that too much competition could cause discomfort and hurt players' motivations. This effect can be seen when a player is not very proactive towards the focal behavior (Klasnja and Pratt 2012). In some other cases, the competitive social condition made no difference, i.e., neither helped, nor hindered the desired behavior (Gasser et al. 2006). As reviewed earlier in the Introduction, the gamification literature on leaderboard effects in training and education also showed mixed findings. The inconsistent results from prior research lead us to conclude that the effects of social comparison elements such as leaderboards would depend on contingent factors, which requires further investigation. However, our review suggests a lack of theoretically grounded empirical studies on this phenomenon, which motivates us to develop an explanatory model based on the social comparison perspective for this purpose.

Social Comparison Theory

It is in the nature of human beings to compare themselves with others to evaluate their own performance (Hoorens and Damme 2012; Suls et al. 2002). Social comparison has been defined as individuals' acquiring information about others to evaluate their own opinions and behaviors (Festinger 1954). Since it is not always easy for people to access objective information for self-evaluation, comparing themselves with others becomes a major approach to satisfy the need for self-evaluation (Festinger 1954).

The direction of social comparison can be upward and/or downward, i.e., whether people compare themselves to better-off or worse-off others (Buunk et al. 1990; Latané 1966) in terms of a variety of dimensions, such as status, capability, and achievements (Shang et al. 2012). Differences in the comparison target selection could produce different affect consequences. Indeed, prior research proposes that the affective consequences of social comparison are not intrinsic to its directions (Buunk et al. 1990). A theoretical model that explains the distinct affective consequences of both directional social comparisons is the identification-contrast model (Buunk et al. 2013). Specifically, upward and downward social comparisons will be associated with positive or negative consequences for comparer’s self-evaluation and affect, depending on whether the comparer mentally regards the compared targets and himself or herself as the same or different, i.e., identification or contrast, respectively (Bailis and Chipperfield 2006). When people compare with better-off others, two signals could be obtained. One is that you are not as well off as others, and the other is that it is possible for you to improve your current status. Conversely, exposure to downward social comparisons also provides two signals, i.e., that you are not as badly off as others, and that you could get worse in the future (Buunk et al. 1990). Comparers who are influenced by the positive aspects of the same information may feel better about themselves, while those who focus on the negative aspects may feel worse. Thus, the affective consequence in response to upward and downward social comparisons depends on how the comparer interprets the information (Bailis and Chipperfield 2006; Buunk et al. 1990).

However, the question then arises, as to when the predominant effect of directional comparisons will result in contrast or assimilation. Previous literature suggests that the environment could have a significant influence on this process (Brown et al. 2007; Collins 2000; Stapel and Koomen 2005). Particularly, an environment that promotes competition is likely to facilitate contrast since it would reward individual accomplishments (Brown et al. 2007), while cooperative environments would promote a mindset in which the emphasis is on the group and thereby result in assimilation effects (Buunk et al. 1990; Stapel and Koomen 2005). In the context of fitness apps, since leaderboards are applied to create competition among users, the contrast effect is likely to dominate. Additionally, the way users interpret
comparison information would naturally differ based on individual characteristics, which will likely affect their attitudes and physical activity behaviors.

Social comparison theory has been applied in the healthcare context, with mixed findings about its effects (Bailis and Chipperfield 2006; Collins 1996; Frieswijk et al. 2004; Taylor et al. 1986; Wood et al. 1985). From prior studies, it is important to note that several variables have been suggested as contingencies that influence the effect of social comparison on health behaviors. These contingency factors could be categorized as environmental and individual factors. As noted earlier, the identification-contrast model explains how the effect of directional social comparison depends on the competitiveness of the environment (Brown et al. 2007). Thus, in our model, we include perceived competitive climate as an environmental contingency that would moderate the effect of social comparison on attitude and subsequent physical activity behavior. Another environmental factor that may influence physical activity behavior directly is the facilitating conditions (Humpel et al. 2002). It includes both social conditions, e.g., friend’s support, and physical environmental conditions, e.g., favorable weather.

As for the individual contingency factors, several variables were identified from the previous literature. A key variable in social comparison studies is perceived control. It refers to the perceived ability to control or change the status of an event (Wu and Srite 2014). Specifically, in the context of fitness apps use, such a perception equates to users’ judgment of their ability to perform the target physical activity and can be conceptualized in terms of the self-efficacy about physical activity (Motl et al. 2000). Thus, self-efficacy is considered as a key moderator in our model. Other individual factors that could influence social comparison outcomes include personality differences among people. In our model, we included self-esteem and social comparison orientation as control variables for this reason.

**Research Model and Hypotheses**

Drawing on the social comparison theory and literature reviewed above, the research model for this study is shown in Figure 1. The dependent variable in the context of fitness apps is the extent of physical activity behavior performed in a fixed time period. Our main independent variable is the frequency of social comparison through the leaderboard, which includes both downward and upward comparisons since users are likely to do both when they view the leaderboard. We further expect that perceived competitive climate and self-efficacy about physical activity will moderate the effect of social comparison on attitude, which in turn affects the physical activity behavior. Facilitating conditions is an additional antecedent that is proposed to influence the dependent variable.

We also included control variables in our model that may affect user’s physical activity behavior, i.e., age, gender, race, BMI, level, leaderboard position, social comparison orientation, self-esteem, and the average difference between a user and his/her closest neighbors in the leaderboard (Mussweiler et al. 2004).

**Figure 1. The Proposed Research Model**

Attitude is defined as a positive or negative view of an “attitude object”, i.e., a person, behavior, or event (Angst and Agarwal 2009; Bernstein et al. 2000). In this study it refers to the individual’s view about carrying out physical activity behavior facilitated by the fitness app. Studies suggest that attitudes are typically formed and modified as people gain and process information about attitude objects (Eagly and Chaiken 1993). Deriving from prior social comparison literature, the frequency of social comparison will influence the emotional response that occurs, i.e., the individuals’ attitude after receiving the message. In the context of fitness apps, leaderboards are included to foster competition among individuals (Yates and
Wootton 2012). As per the identification-contrast model (Buunk et al. 2013), such a competitive element is likely to promote contrast effects among individuals. Hence, when a user often engages in social comparison via the leaderboard, contrast effects would make him or her interpret such information either positively or negatively depending on the relative strength of downward versus upward comparison. Further, as mentioned before, the effect of social comparison on attitude would depend on several contingency factors, including environmental and individual factors.

A key environmental factor identified earlier is the perceived competitive climate, which refers to the degree to which individuals perceive outcomes to be contingent on comparisons of their performance against that of their peers (Brown et al. 1998), in this case the relevant outcomes could be the person’s image and status among peers based on their physical activity behavior recorded on the fitness app. Prior research has found that the response to peer comparison in a game would at least partly depend on the perception of competition from peers in the same round (Sepehr and Head 2011). This suggests an interaction effect between perceived competitive climate and social comparison on users’ attitude. In the context of social comparison via leaderboards, though contrast effects are expected to dominate, such effects would be perceived differently among individuals. If a user does not perceive a competitive climate when confronted with leaderboard information, even if he/she engages in comparison frequently, the effect on attitude may not be strengthened. In contrast, if the user perceives a strong competitive climate, this can strengthen the judgment about the contrast effects against competitors. In this condition, frequent social comparison can have a greater impact on attitude. Thus, we hypothesize,

H1: Perceived competitive climate will positively moderate the effect of social comparison via leaderboard on user’s attitude

Moreover, the relationship between the frequency of social comparison and user’s attitude can be moderated by individual factors. Deriving from the discussion presented earlier, a key contingency factor is individual’s self-efficacy. It is defined as people’s judgment of their ability to accomplish the desired behavior (Bandura 1986), that is interpreted as an individual’s self-confidence in his/her ability to perform a behavior (Bandura 1982). For fitness app users in our study, this construct refers to their confidence in attaining the desired physical exercise performance, such as covering a certain distance or running more frequently. Those who have high self-efficacy about the physical activity usually feel that they have the means to attain a high level of functioning, as well as avoid a downfall. For individuals high in self-efficacy, prior research has suggested that downward or upward comparisons would pose less of a concern (Buunk et al. 1990), that would more likely yield positive emotional responses. Thus, whichever the direction of social comparison, the effect on attitude will be weakened if the individual has a high level of self-efficacy about physical activity. Thus, we propose that,

H2: Self-efficacy will negatively moderate the effect of social comparison via leaderboard on user’s attitude

In addition, facilitating conditions is an environmental factor that should directly affect physical activity behavior (Humpel et al. 2002; Triandis 1979). It reflects the availability of resources needed to engage in a behavior, such as time, money and other specialized resources. In the context of our study, facilitating conditions consists of two dimensions. The first dimension represents the social environment for the physical activity, e.g., the support of government and the social network (Lu et al. 2008), while the second dimension describes the physical environment for exercise such as facilities and weather (Humpel et al. 2002). Physical activity behavior is more likely to occur if the facilitating conditions make it easy to do so. Thus, we hypothesize,

H3: Facilitating conditions will be positively related to user’s physical activity behavior

Last, a consistent relationship between attitudes and behaviors is well-documented (Ajzen 1985; Angst and Agarwal 2009), i.e., a positive attitude is associated with a greater extent of the behavior, and in contrast, negative attitude reduces the possibility of the relevant behavior. In the context of our research, physical activity behavior is assessed from users’ activity records i.e., via objective data from the fitness app. The relationship between attitudes and target behaviors derives from the basic human need to achieve cognitive consistency (Festinger 1962) such that attitudes and behaviors should be aligned with each other. Therefore, we propose that,

H4: Attitude towards physical activity will be positively related to the physical activity behavior
Methodology

We carried out a preliminary test of our model using survey and objective data from users of the Nike+ Running app, which is an Android and iOS healthcare mobile app that is widely used to track distance, pace, time and calories burned when working out. We chose the Nike+ Running app because of its popularity (Comstock 2013) and gamification elements, that allow us to examine the effect of leaderboards on users’ physical activity behavior. Other than leaderboards, the Nike+ Running app also incorporates levels and badges to motivate users. However, unlike leaderboards, which allow for direct and immediate comparison among individuals, the other elements are more often indicators of personal achievement and may need more effort i.e., go to their friend’s profile to check their badge or level, to carry out social comparison. Nevertheless, we included users’ level (as badges are correlated to levels) as a control variable in our model to account for its effect.

While the app is appropriate to test our model, the publicly-available APIs provided by the Nike+ Running platform are insufficient for our research purpose i.e., there were no APIs for accessing users’ leaderboard, exercise records, and levels. Hence, we employed an alternative method to collect the objective data for the study. Specifically, we provided a piece of JavaScript code to our participants, which they were required to execute on their Nike+ Running web pages. This code enabled us to crawl the participants’ objective data and transmit it to our server. Additionally, subjective data was collected from the participants via an online survey. The subjective and objective data were collected as per the method and measures described below.

Data Collection

To recruit our subjects, we posted a call for participation on the bulletin boards of a few large public universities in China and Singapore. As students are a common user group for this kind of app (Price 2014), this sample is appropriate for our study. The requirements for participating in the study were that the students need to be existing Nike+ Running users with at least one month of history records and at least 2 friends in their profile. They were also required to be familiar with web browser usage and able to run the JavaScript code we provided. Through this method, we were able to recruit 80 Nike+ Running users as our participants (after validating that they satisfied the study requirements). They were given $15 after successfully completing the data collection steps.

Our data collection was divided into two online sessions, with a gap of one month apart. This allowed us to have a time lag between our independent and dependent variable measurements, where the independent and control variables were captured in the first session and only the dependent variable, i.e., the physical activity behavior during the past month, was assessed via the second session. To facilitate the data collection, we provided a website to guide the participants. On the website, we gave detailed instructions for the steps that the participants must follow to complete the two sessions as well as the JavaScript codes for objective data collection. Since the instructions were provided in detail on the website, participants were asked to follow them on their own and contact us if they had any problems. The two online sessions had some common steps, where the participants were first required to login to the Nike+ Running website, followed by executing the JavaScript code we provided, such that their objective data e.g., the workout record, would be transmitted to our server. Additionally, for the first session, the webpage then automatically directed the participants to an online survey (Google form was used as the primary survey platform, and Qualtrics as an alternative for participants in China, where Google services are sometimes blocked), used for collecting their subjective and demographic data.

The data collected in the first session included all the subjective constructs (i.e., social comparison, attitude, perceived competitive climate, self-efficacy for physical activity, facilitating conditions, social comparison orientation, and self-esteem), demographic information (i.e., age, gender, race, BMI), and objective data (i.e., levels, physical activity records, position in leaderboard, and the average difference between an user and his/her closest neighbors shown in leaderboard). The data collected in the second session was the workout performed in that period, which was used to calculate the physical activity behavior (times run / distance run) during the elapsed month. Between these two online sessions, the participants just used the Nike+ Running app as usual.
Construct Measurements

Our dependent variable, *physical activity behavior*, was measured by how many times a participant ran during the period of 1 month between the two data collection sessions (we also collected data on the distance ran in the same period and tested the model with either distance ran or the ratio of distance ran/frequency as the dependent variables, but we got similar results). The survey items for this study were developed by adapting existing measures to our study context, as they could not be used as is (as shown in Table 1). Except where mentioned otherwise, all items were measured using a 7-point Likert scale anchored from “strongly disagree” to “strongly agree”.

**Table 1. Measurement Items of Subjective Constructs**

<table>
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<tr>
<th>Construct</th>
<th>Item 1</th>
<th>Item 2</th>
<th>Item 3</th>
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<tbody>
<tr>
<td>Attitude (Adapted from Osgood et al. 1957, Angst and Agarwal 2009)</td>
<td>What are your feelings about performing physical activity supported by the app? (1 to 7 scale)</td>
<td>Facilitating Conditions (Adapted from Thompson et al. 1994, Lai et al. 2008, Humpel et al. 2002)</td>
<td>The government encourages me to exercise more and keep fit</td>
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<tr>
<td></td>
<td>• Bad to Good</td>
<td>My social network (e.g., family, friends, colleagues) encourages me to exercise more and keep fit</td>
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<td></td>
<td>• Boring to Exciting</td>
<td>Fitness apps are available for promoting physical activities</td>
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<td></td>
<td>• Unpleasant to Pleasant</td>
<td>Specialized training is available to me concerning how to exercise appropriately</td>
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<tr>
<td></td>
<td>• Dislike to Like</td>
<td>Facilities for physical activities (e.g., a cycle path, a local park) are accessible to me</td>
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<tr>
<td></td>
<td>• Unimportant to Important</td>
<td>Opportunities for physical activities (e.g., home equipment, presence of sidewalks) are available to me</td>
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<td></td>
<td>I can be physically active on most days no matter how busy my day is</td>
<td>The weather is favorable for physical activities</td>
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<tr>
<td></td>
<td>I can be physically active during my free time on most days even if I could watch TV or play video games instead</td>
<td>Social Comparison Orientation (Gibbons and Buunk 1999; Shang et al. 2012)</td>
<td></td>
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<tr>
<td></td>
<td>I can be physically active during my free time on most days even if it is hot, cold or raining outside</td>
<td>I often compare how I am doing with other people</td>
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<tr>
<td></td>
<td>I can be physically active during my free time on most days</td>
<td>If I want to find out how well I have done something, I compare what I have done with how others have done</td>
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<td>Self-efficacy about physical activity (Adapted from Motl et al. 2000)</td>
<td>I often compare myself with others regarding what I have accomplished in life</td>
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<tr>
<td></td>
<td>I always pay much attention to how I do things compared with how others do things</td>
<td>I often compare myself with others regarding what I have accomplished in life</td>
<td></td>
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<tr>
<td>Social Comparison (Adapted from Brown et al. 2007)</td>
<td>The amount of recognition I get within my social network in this fitness app depends on how my rank on leaderboard compares to others</td>
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<tr>
<td></td>
<td>Please indicate the frequency with which you compare yourself to others who are below you in the leaderboard in this app (1=never to 7 extremely often)</td>
<td>Everybody I know is concerned with their rank on the leaderboard</td>
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<td></td>
<td>I feel that I have a number of good qualities</td>
<td>My friends within this fitness app frequently compare their results of physical activity performance with mine</td>
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<td></td>
<td>I take a positive attitude towards myself</td>
<td>Others within this fitness app frequently compare their results of physical activity performance with mine</td>
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<td>I feel that I am a person of worth</td>
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<td>On the whole, I am satisfied with myself</td>
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Data Analysis and Results

We used SPSS version 22 to perform exploratory factor analysis (EFA) and validate our measurement
model. Subsequently, SmartPLS2 was used to test our structural model of Figure 1. Due to lack of space, the descriptive statistics and EFA results are not included here. However, all but four factor loadings were above 0.7 (the minimum was 0.64), and the cross-loadings were much lower than the factor loadings (the maximum was 0.45). The composite reliability and Cronbach’s Alpha values exceeded 0.7 for all multi-item constructs (minimum values were 0.81 and 0.72, respectively), and the average variance extracted (AVE) values exceeded 0.5 (minimum value was 0.53). Further, cross-correlations between constructs were below 0.6 (the maximum was 0.56) and were less than the root of AVE of corresponding constructs (see Table A1 in the Appendix). Thus, our constructs exhibited adequate convergent and discriminant validity (Fornell and Larcker 1981; Nunnally 1978).

Our hypotheses testing results are summarized in Table 2. The results indicate that all four hypotheses were supported. Consistent with our hypothesis, facilitating conditions positively affect fitness app user’s physical activity behavior. Further, user’s attitude has a significant positive effect on their actual physical activity behavior. Thus, H3 and H4 were supported. As for the moderating effects, perceived competitive climate was found to positively moderate the relationship between social comparison and user’s attitude, which is consistent with H1. On the other hand, self-efficacy about physical activity negatively moderates the relationship between social comparison and attitude, which is consistent with H2. In addition, several controls, i.e., age (positive effect), gender (male is stronger), BMI (negative effect), race (non-Chinese is stronger), levels (positive effect), and average difference (negative effect) were significantly related to the dependent variable. Overall, the model could explain 20.5% of the variance in attitude and 43.0% of the variance in physical activity behavior.

<table>
<thead>
<tr>
<th>Table 2. Results of Model Testing</th>
<th>Coefficient</th>
<th>T-value</th>
<th>Hypotheses</th>
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<tr>
<td>Social Comparison -&gt; Attitude</td>
<td>-0.045</td>
<td>0.655</td>
<td>-</td>
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<tr>
<td>Perceived Competitive Climate -&gt; Attitude</td>
<td>0.175**</td>
<td>3.348</td>
<td>-</td>
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<tr>
<td>Self-Efficacy about Physical Activity -&gt; Attitude</td>
<td>0.288**</td>
<td>8.422</td>
<td>-</td>
</tr>
<tr>
<td>Social Comparison * Perceived Competitive Climate -&gt; Attitude</td>
<td>0.150**</td>
<td>4.151</td>
<td>H1 supported</td>
</tr>
<tr>
<td>Social Comparison * Self-Efficacy about Physical Activity -&gt; Attitude</td>
<td>-0.187**</td>
<td>2.123</td>
<td>H2 supported</td>
</tr>
<tr>
<td>Facilitating Conditions -&gt; Physical Activity behavior</td>
<td>0.098**</td>
<td>3.213</td>
<td>H3 Supported</td>
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<tr>
<td>Attitude -&gt; Physical Activity behavior</td>
<td>0.056*</td>
<td>1.689</td>
<td>H4 Supported</td>
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Note: *p < 0.01, **p < 0.001

Contributions and Future Plan

Although gamification elements, and specifically leaderboards, have been widely used in fitness apps, there is a lack of research aiming to understand the effects of these elements on desired user behaviors. Our study makes several theoretical contributions in this regard. First, the study adds to the literature by developing a model built on social comparison theory that explains how social comparison via leaderboards influences fitness app users’ attitudes and in turn, physical activity behaviors. Second, our model uncovers salient environmental and individual factors that are found to moderate the effects of social comparison on user attitudes. Third, as a departure from prior work, the social comparison construct in our model includes both upward and downward comparisons since users are typically seen to perform both forms of comparison together in our study context. Last, our empirical test using subjective and objective data to assess relevant variables, and controlling for alternative explanations, shows good support for our model.

Practically, this study aims to provide insights for fitness app developers on the impacts of a key gamification element i.e., a leaderboard. Our findings suggest that developers should be aware of both direct and contingent effects when intending to employ leaderboards in their app design. Specifically, social comparison through leaderboards influences attitude under low to moderate self-efficacy and moderate to high perceived competitive climate conditions. Thus, the appropriate conditions are required for leaderboards to have their desired effects. At the same time, our findings on control variables also inform fitness app developers about other factors that influence the target behavior, i.e., these additional factors would also need to be accounted for in driving the desired behavior.
As a research-in-progress paper, our model and findings need further validation. First, due to the effort required to participate in our study (i.e., take part in two online sessions and run the Javascript codes in addition to completing the survey), it is challenging to recruit qualified participants. Thus, our sample size was limited and needs to be further expanded by targeting other student and young adult groups. Nevertheless, the sample size of 80 is adequate to provide us preliminary findings on the effects of social comparison via leaderboards in fitness apps. Second, besides Nike+ Running, there are other fitness apps available in the market, with somewhat different functions, e.g., RunKeeper and Fitbit. In order to derive more generalizable results, it will be valuable to recruit participants from other fitness apps to test our model. Last, as gamification elements are typically not used separately but in combination (Kankanhalli et al. 2012), it is important to further examine how leaderboards may have complementary effects with other gamification elements.

**Appendix**

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<th>Table A1. Correlation Table</th>
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Reference


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Gamification in Fitness Apps


