The Influence of Fictitious Community Trend on Individual Physical Activity

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Abstract
In recent years, many people's life style has gradually become sedentary, and therefore lack of physical activity. While there are many applications that encourage physical activity through social interaction (such as rankings, sharing, or messaging), few of them have shown that community composition and trends can help people do more physical activity. Here, we created fictitious communities with different trends to investigate how different community trends affect users. We found that most of the participants in the growth community had more walking steps and all participants in the decline community had fewer walking steps than before. The fictitious community trend displayed through the leaderboards might allow our participants to experience the process of social learning and social comparisons implicitly and then change their intentions and behaviors. The results of this study provide some design implications for building fictitious communities in mobile applications to encourage users to do more physical activity.

Author Keywords
Physical Activity; Social Comparison; Social Learning; Fictitious Community; Leaderboard

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous

Introduction

In recent years, technological advances have enabled us to do many things on the Internet, such as chatting, shopping and working, so as to reduce physical activity in the real world. Sedentary has become the way of life for many people [12]. In the population, office workers have fewer opportunities for physical activity than young people or students and are more likely to suffer from chronic diseases [2]. In response to this situation, more and more applications of health technologies have been developed to promote physical activity [4, 10, 11, 13].

One way to promote physical activity is to use social motivations in persuasive technology [9]. People often care about their own image in the eyes of others, and show the behavior in line with social expectations. Many existing applications incorporate community mechanisms that allow participants to see each other's performance and rankings in order to encourage more physical activity. Applications such as Nike Plus, Fitbit, and Walkr provide users with a community leaderboard that allows users to understand their and other people’s physical activity performance.

Although social motivation is considered to be useful for promoting physical activity, some studies have shown different results. When Zuckerman and Gal-Oz [15] developed an application prototype, StepByStep, to examine the different effects of an application with or without a leaderboard in encouraging physical activity, they found that the application with the leaderboard did not significantly increase a person's Physical activity. Consolvo, et al. [3] also claim that there is little evidence that community rankings can improve people's physical activity. The impact of the community on each user may not be clear. For example, in real life, users can not change the communities in which they participate. Community trends are beyond our control, so the impact of the community is not easy to understand. The impact of the community may be beneficial, but it may also be harmful. However, we may build a fictitious community to more effectively encourage users to do physical activity by using social bots [7].

In this study, we conducted an experiment to investigate whether fictitious communities can be used to change the user's physical activity and how the fictitious community affects the physical activity of office workers by observing their daily walking steps. We then conducted a post-interview to see how community trends could help people change their intentions which underlie the observed behavior. We expect the results of this experiment to provide recommendations for the design of fictitious community mechanisms for health promotion applications. Designers can use the results of this study to create a more appropriate community for each user, and help people to more effectively carry out more physical activity.

Methods

Participant

The IPAQ (International Physical Activity Questionnaire) was distributed on the Internet Forum (PTT, Taiwan's largest terminal-based bulletin board system). Based on the results of the questionnaire, we contacted 55

office workers with insufficient physical activity (less than 600 METs per week), and finally, eight participants were recruited in our experiment.

Experimental Apparatus

Bandura and McClelland in social learning theory [1] pointed out that when people and their communities are similar, they are more likely to have learning behavior. And, people tend to take those who are slightly better than themselves as a role model. Therefore, the study provided each participant with a fictitious community similar to their physical activity, based on his or her average number of steps per day.

Figure 1 shows examples of the trend of fictitious community in our study. The fictitious communities and their trends were decided by the following rules. We first used the normal distribution function to generate 29 numbers (the function uses the walking steps of the participant as the mean, and 1/3 of the mean as the standard deviation). These 29 values were the 1st day's walking steps for each of the 29 fictitious participants. For each fictitious participant, the daily walking steps after the first day were determined by the following rules. We used the normal distribution function (mean: the first day walking steps of the fictitious participant. Standard deviation: 1/3 of the mean) to generate nine values. These nine values were then added to the t parameter, *t*, and the sums were then randomly assigned as the number of walking steps per day for the next nine days from the second day to the tenth day. *t* is a parameter that controls the trend of fictitious community and its speed. In this study, there were four experimental groups with different community trends and speeds:

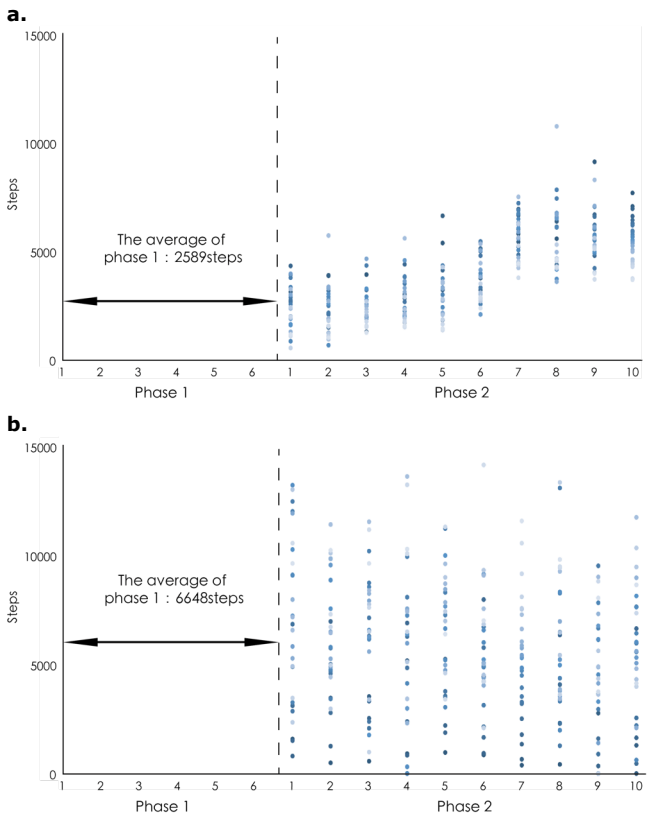

Figure 1: Examples of trend of fictitious community. **a.** The fictitious community of rapid growth group for Participant A1. **b.** The fictitious community of slow decline group for Participant C1. The blue dots represent the waling steps of 29 fictitious participants.

A. Rapid growth group: $t = 100 \times 2^{(day-2)}$ (day = 2, 3, 4, 5, 6, 7 for each consecutive day. After 7, day is maintained at 7). Figure 1a shows rapid growth

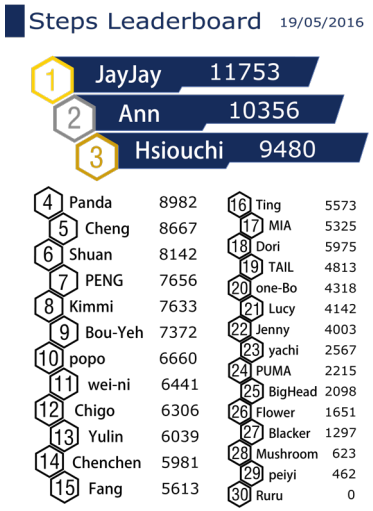

Figure 2: The leaderboard is listed the rank of daily walking steps of 29 fictitious participants and the human participant.

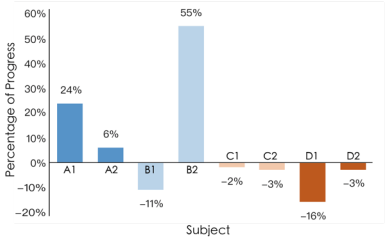

Figure 3: seven of eight participants showed the same trend with the fictitious community behavior. the percentage of progress is calculated by the function: step(phase 1-phase 2)/step(phase 1)

group. The blue dots represent fictitious participants. This fictitious community is for participant A1.

B. Slow growth group: $t = 100\times2\times(day-2)$ (day = 2, 3, … to 10 for each consecutive day).

C. Slow decline group: $t = -100\times2\times(day-2)$ (day = 2, 3, … to 10 for each consecutive day). Figure 1b shows slow decline group. This fictitious community is for participant C1.

D. Rapid decline group: $t = -100\times2^{(day-2)}$ (day = 2, 3, 4, 5, 6, 7 for each consecutive day. After 7, day is maintained at 7).

Two participants were randomly assigned to each of the four different fictitious community groups. Mi Band Standard Edition (http://www.mi.com/en/miband) was used to record the number of steps a participant walks each day. This version of Mi Band only provides information about walking, time, distance, calories, and sleep time. Before the experiment, we informed each participant how to wear the Mi Band, and to ensure that they know how to operate the application, Mi Fit. Then every day, we displayed the walking steps for everyone in the community (including fictitious participants and the participant) on the leaderboard (Figure 2).

Experimental Procedure

During the experiment, the participant must wear the Mi Band every day and reported the total number of walking steps in the previous day to the researcher through Facebook Messenger (a screenshot of the daily record page). Each participant was familiar with the Mi Band, its applications, Mi Fit, and experimental procedures with two to three days. A two-phase experiment was then initiated.

A total of six days of the phase 1 was used to determine the daily walking baseline of the participants. Participants did not get the leaderboard in this phase. Then, the second phase has 10 days (not including weekends and holidays). In the phase 2, the participants were given the leaderboard on a daily basis. This experiment recorded the number of walking steps per day to see if participants were affected by community trends. After the experiment, the participants were interviewed to understand whether the participant's lifestyle and behavioral intentions of physical activity changed.

Result and Discussion

The effect of fictitious community trend on physical activity

This study shows that four different types of community trends (A, B, C, D) have different effects on individual behavior in physical activity. All participants in groups A, C, and D followed the trend of their community, but one participant in group B behaved in the opposite direction to the community (Figure 3). B1's behavior was inconsistent with the community may be because he had different intentions than the others. Figure 4 and Figure 5 show the daily performance of all of our participants. They show that participants had different subtle behavioral tendencies.

The aim of this study is not only to discuss whether the leaderboard could help people as previous studies [3, 5, 15] did, but also to further understand the strategies underlying each participant's walking performance by analyzing the interview transcripts. According to the interview, B1 thought it would be nice if he was not the last person on the leaderboard. B1 said "*I look at the rankings and the number of steps every day, but also*

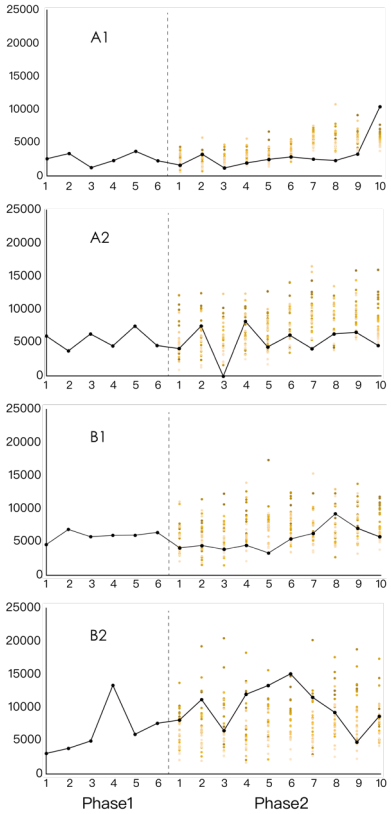

Figure 4: the performance of growth group A, rapid growth group, and group B, slow growth group. X axis: days, Y axis: steps. The black line shows participants' performance. The yellow dots were the walking performance of 29 fictitious participants.

to see who came in front of me, who is behind me and I think as long as I am not the last one, it does not matter, there are many people lazy than I am". We did not find that the different speeds of community trends had different effects on participants' walking steps. When comparing rapid growth groups with slow growth groups, A group's participants did not have more walking steps than the B group's participants. It may be because we have too few samples or other reasons. We will continue to explore the effect of the speed of community trend on behavior in the future.

Implicit Effect of Fictitious Community

While trends of fictitious communities may affect individual behavior, some participants said they did not know that the steps of fictional competitors were increasing or decreasing. Even if the behavior of some of our participants had changed, in the interview they still claimed that their performance would not change because of the existence of the list. This result shows that when people are in the community, the impact of the group may be slow, subtle or unknown. While this requires further investigation, this result is in line with the theories showing the process of behavioral and attitude change may be implicit [6, 14]. C2 described: "*I think there are no differences between more than 3,000 steps and more than 6,000 steps, and I do not find myself doing anything more or less.*"

Social learning and self-efficacy in Fictitious Community

Social learning theory [1] emphasizes the importance of the concept of modeling, or learning by observing a behavior. People can learn by observing the behavior of others and transforming others' behavior into their own behavior. In this study, however, the leaderboard only provided nicknames, rankings, and walking steps so that participants did not have access to more information about other participants, such as who they were, their personality, their occupation, age, walking time, the benefits of their walking. Our participants might wonder why and how other people could walk so much. Although they might want to follow the behavior of others, they could not get enough information to know how to do it. In the interview, we heard a similar situation described by the participants: "*Actually, I'm curious about people who always come out at the top, and I just want to know how they did it*" (D1). In addition, some participants mentioned that if the competitors are their friends or significant others, they would ask them how to achieve the daily amount of physical activity. For example, D2 said: "*If he is my friend, I would call to ask him why you can walk so many steps yesterday, what were you doing? I would also like to know more about how many steps each time point displayed on his Mi Fit. Moreover, if I know the people on the leaderboard, I would have a greater intention to go beyond them*".

Self-efficacy reflects the individual's understanding of his/her ability to achieve a goal performance in a community [1]. For example, A1 had 2,000 to 3,000 steps per day in the first and second phases. Surprisingly, he got 10,467 steps on the last day of the experiment. A1 said: "*When I see someone else can walk more than 10,000 steps, I have a strong intention to achieve this goal, too. This is not just a bunkum. I think if others can do, I have the ability to achieve it.*" This interview result indicates that the achievement of others is likely to make people more confident to achieve their goals.

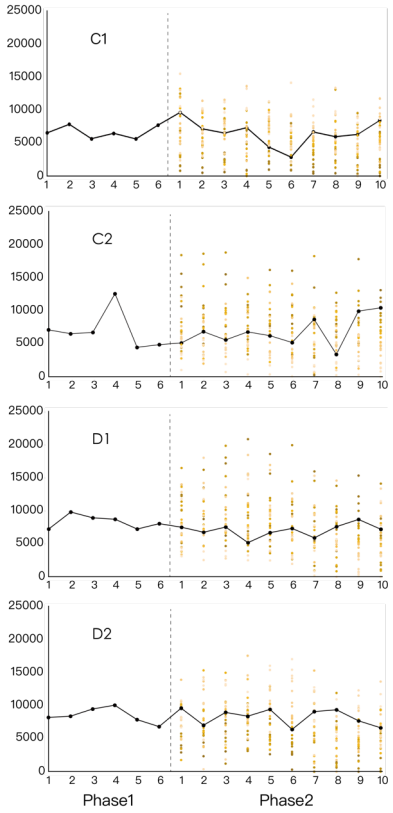

Figure 5: the performance of growth group C, slow decline group, and group D, rapid decline group. X axis: days, Y axis: steps. The black line shows participants' performance. The yellow dots were the walking performance of 29 fictitious participants.

Social Comparison in Fictitious Community

The social comparison theory [8] suggests that people evaluate their abilities and form self-evaluations by observing the performance of others. The results of our interviews indicate that participants would see walking steps at the top and bottom of the leaderboard to understand the difference between themselves and others. They determined their level by looking at the leaderboard: "*When there is a leaderboard, I want to take more steps, even though a little more steps are better than no more steps. I see I'm always at the bottom of the leaderboard, which seems to mean that my physical activity is not enough. I would look at my rankings and know the difference between myself and others*" (A2). One participant thought that people have high rankings as imaginary enemies and thought it is an interesting way to encourage herself to take more walking steps: "*Exercise is a very boring thing. Especially, if you want to lose weight, you need to increase a little bit of movement every day. So, I think it is very important to find fun, [...]. In other words, some of the imaginary enemies can bring me more fun*" (B2).

Interestingly, some participants did not set up an imaginary enemy. Their strategy was to first see the overall walking steps of the community and then set their goals to the average performance of the community. They wanted to maintain their performance in the middle of the community, rather than becoming the front or bottom of the rankings: "*[...] For example, people in the community do not seem to like sports, if your ranking is always the first, it would be very strange! Well, people may think of you as a benchmark ... may go to work harder, but I do not like it! It made me feel like I was going to be discussed.*" (C2).

Conclusion

This study creates a fictitious community based on the average walking steps of each participant and four community trends to explore how trends in the fictitious community affect individual daily walking steps. We found that even if the participants did not know the people on the leaderboard of the fictitious community, the participants' performance would follow the community trend. Individuals may set their behavioral strategies by looking at the leaderboards and then implicitly changing their intentions through learning and comparing their own performance with others on the leaderboard. We found that sometimes behavioral changes may be very subtle and even the participants do not know that they have changed. These results show the potential for using fictitious community to encourage people to do more physical activity. For example, while most people do not know the majority of online games, their motivation to play games is still affected by other people. In a sense, the people of these online games may not exist for the individual in the real world. However, people can still invite their true friends to the community, in which a proportion of virtual players or social robots can motivate people to work harder to achieve their goals. The current study only investigates how a fictional community affects individuals. In the future, we can use fitness technology to monitor the current activities of a group of friends in order to design a suitable mixed community for this group to encourage them to improve their physical activity and stay healthy.

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