The Effect Factors on Sustained Use of Physical Activity Apps

Completed Research Paper

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Abstract

The physical activity apps have been used as intervention tools to improve public exercises. However, this type of intervention is difficult to sustain even on those have already stimulated to exercise in real-world conditions. Motivated by this, we develop a theoretical framework to explain the discontinued use of physical activity apps with app type preference and past behavior as predictors based on modern habit theory. In which, the app type preferences are distinguished by genders based on the social role theory. These analyses are conducted using a one-month app use data from 10,263 samples, which are collected from a Chinese mobile carrier. The results suggest that different genders prefer distinct PA app types. The initial engagement on PA apps and the consistency of users preference may promote the sustained use of apps.

Keywords: Physical activity apps, sustained use, past behavior, gender

Introduction

A large number of physical activity (PA) apps are designed to modify un-health behaviors. These apps, benefited from the development of mobile technology, provide multiple functions to promote exercises, such as distance tracking and customized exercise plans (Sama, Eapen, Weinfurt, Shah, & Schulman, 2014). Benefit from the convenient and the potential positive intervention of PA apps for physical activities, the commercial companies, government agencies, and the public tend to use these apps as tools to improve public health (Santoro, Castelnuovo, Zoppis, Mauri, & Sicurello, 2015; Zhao, Freeman, & Li, 2016). However, the engagement and intervention performance of these apps in real-world conditions are not satisfying. The app-based intervention may be effective for short-term behavior change but fail to support sustaining behavior (Marshall, Owen, & Bauman, 2004). Therefore, it is necessary to explore the sustained use of PA apps in real-world conditions.

Previous studies have analyzed the factor to promote PA app use. They find that the adoption and engagement of apps are affected by app interfaces, app functions and individual attributes (Cho, Park, & Lee, 2014; Tang, Abraham, Stamp, & Greaves, 2015). The sustained use of apps can be predicted by users' perceived benefit and the customization functions that user engaged (Cheng, Lin, Nijhawan, Westhem, & Bernstein, 2017; Serrano, Coa, Yu, Wolff-Hughes, & Atienza, 2017). However, there still exist several gaps in this issue. First, there are too many PA app available for users to choose in real-world. As shown in Jahns (2014), there are more than 100,000 health-related apps in two leading app platforms (IOS and Android). It is hard to know which app that user prefer to adopt and sustained use. Second, the engagement on PA apps combines with physical health behavior. The process from engagement to sustained use may accompany with new habit formation process. This may require a more theoretical foundation to explain the process.

In this regard, this paper aims to explore the app type adoption differences and analyze the relationship between the sustained use and PA app type preference, engagement behavior respectively. At first, we classify the most popular PA apps in China into three types and identify the consistent app defined target exercise and user used purpose. Next, we explore the app type preferences by genders. Finally, we analyze the relationship between app sustained use and app type preference, past behavior respectively. In this preliminary study, the analysis is conducted by using PA apps use data of 10,263 samples in one month from one of the Chinese biggest mobile carriers. The results indicate that the app preference and past behavior may affect the long-term sustained app use. This study contributes to the literature by expanding the long-term PA app engagement and providing insights on how to promote exercise habit formation.

The remainder of this paper is organized as follows. Next section reviews relevant works about PA app engagement and Behavior change technologies. Then, we present the research framework and hypotheses. Section method describes the data collection, app type identification method, and variable measurements in this study. The followed section presents the experiment results of this study. Finally, the last section summarizes the initial contributions, limitations, and future work.

Literature Review

The sustained use of PA apps has been proved to have satisfied performance under experiment conditions (Quested et al. 2017). The optimization of the effectiveness and the intervention performance of these apps attracts more and more attention.

Effect Factors of PA App Engagement

Some studies find that user attributes may affect app engagement. Individuals' attitude, health consciousness, perceived usefulness, health information orientation, and personal exercise motivations could determine the adoption and sustained engagement of health-related app (Cho et al. 2014; Kwon et al. 2017; McGloin et al. 2017). In addition, the preference of the way to deliver health behavior intervention (such as web-based, face-to-face) is different among different genders and ages, which may result in the engagement inconsistent among app users (Short et al. 2014).

Some studies find that the interface and function design of the app may affect users' perceived effectiveness of apps. Tang et al. (2015) find that the behavior change techniques (BCTs) and app design features, including the structure, personalized features, and easy to use could improve the sustained use and the intervention effectiveness of a weight-control app. Zhao et al. (2016) review the studies on health behavior change by mobile phones. They suggest that less time consumption, real-time feedback, and user-friendly design can improve the effectiveness of app intervention.

Behavior Change Technologies on PA Apps

For short-term behavior change, interventions that considered BCTs are associated with better physical activity performance. The most common used BCTs in mobile apps are feedback, monitoring, goal setting, rewards, and social support (Conroy et al., 2014; Bondaronek et al., 2018). These technologies, also called self-regulatory behavior change techniques, can support users to set up exercise goals, monitor exercise results (e.g., walking steps), and obtain virtual rewards and supports by achieving objectives (Sullivan and Lachman 2017). For long-term behavior change, although some studies suggest that the customized BCTs is related to longer-term app use (Serrano et al. 2017), the relationship between BCTs and long-term exercise adherence is unclear. Some studies proposed that these technologies provide healthy lifestyle skills, which may only affect on the primary stage of health behavior formation (Murnane et al. 2015) After the intervention, participates only accumulate health-related knowledge (Choe et al. 2017) However, there also exist users that could comply with the instructions of BCTs and prolong the usage duration (Lee et al. 2018; Serrano et al. 2017). These findings suggest that how user use the PA app may affect the performance of BCTs interventions and it may require other theory to explain the long-term app usage behavior.

To sum up, the prior studies on physical activity apps have found that the design of apps and individual traits may influence the engagement of the apps. However, these studies still have several gaps when employing on the real world. First, most studies rely on self-reported data from surveys and interviews, which are severely biased due to social desirability motivations. Second, these studies often focus on one app platform at one time, which yielded mixed and often inconsistent findings. Third, these studies contain limited theoretical foundation to support the sustained use of PA apps, which may lack reasonable research paradigm. At last, the real-world conditions are complex, the effectiveness and the effect factors of the engagement of physical activity apps require more evidence. In this study, the analyses are using mobile data, which contains the objectively use logs of physical activity apps. The data are recorded by mobile carriers to provide telecommunication services, which can break the limitation of the multi-platforms.

Research Framework and Hypotheses

Habit learning represents forming context-response associations in memory by repeated responding. And the performance of habit should be targeted automatically. In order to realize the long-term behavior performance, it is necessary to form the new behavior habit (Renfree et al. 2016). However, the habit formation process is a challenging process (Wood and Neal 2007). Unlike the short-term behavior change which is stimulated by specific motive and goal, long-term habit behavior is associated with the internal memory and intrinsic motive (Walker et al. 2015). Old habits are always triggered unconsciously under the specific context, regardless of how strong the new behavior generation willingness is (Carden and Wood 2018; Pinder et al. 2018). By repeating the new action under a particular context, the internal memory about the implicit connections between the specific context and new behavioral response could form (Carden and Wood 2018). With the repeating, new behavior could be more likely to stimulate by the intrinsic motive other than external motive, which could benefit the new behavior acts unconsciously (Wood and Rünger 2016).

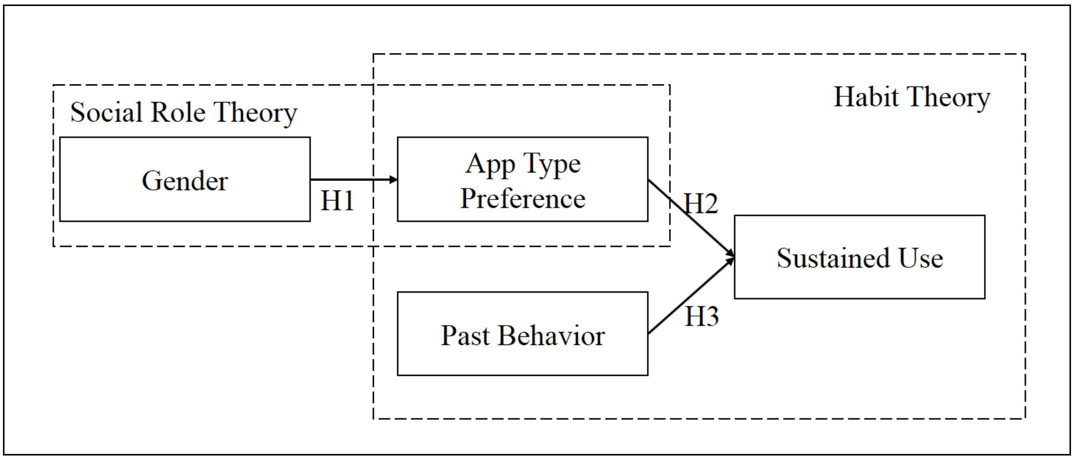

Figure 1. The Research Framework

For PA app users, users' external motivations may stimulate them to download PA apps and use for the first time. After the initial experience, users' internal dispositions and habit learning response from every behavior repeated process may promote the sustained learning process. Therefore, for PA app situation, we suggest that the app type preference and the past behavior as predictors to the sustained use. The app type preference reflects the users' internal disposition. And the past behavior indicates the repeated behavior on PA app. According to this process, we propose the research framework as depicted in Figure 1.

Gender Differences in App Types

Social roles theory suggests that different social roles occupied by men and women may result in gender differences (Eagly and Wood 1999). The gender differences are also reflected in physical activity. Especially, men prefers vigorous exercise and participating in sports teams (Sallis et al. 1996; Vilhjalmsson and Kristjansdottir 2003). They are more likely to do regular, sustained, and high strength exercise (Caspersen et al. 2000). Women concern more about physical appearance, lose weight, and eating issues (Mast and Hall 2006; Pliner et al. 1990). The exercise frequency and strength may be lower than those from man (Vilhjalmsson and Kristjansdottir 2003). They prefer moderate exercises and activity-related lessons and classes (Caspersen et al. 2000; Sallis et al. 1996).

Drawing on the definition of Sama et al. (2014), McGloin et al. (2017), as well as the popular app rank list in China (Enet, 2018), we classify the PA app used in this study into three categories: fitness/training, diet/caloric intake, and distance tracking. For fitness/training, this type of apps usually provides physical fitness and training services with courses and videos that users can follow these to exercise (Sama et al. 2014). These services satisfy the preference for women in activity-related lessons and the appearance attention as discussed above. Thus, we propose that:

H1a. Compared to men, women are more likely to use fitness/training apps.

For diet/caloric intake, weight control has been proved as a stronger exercise motivation for women (Louw et al. 2012). And women are more concerned about the services provided by diet/caloric intake apps, including calories tracking, meal planning, videos, and alternative dietary (Sama et al. 2014). Reasoning from these, we hypothesize that women are more likely to adopt these apps:

H1b. Compared to men, women are more likely to use diet/caloric intake apps.

For distance tracking, the services usually contain walking and running trajectory tracking. The strength of activities contains both moderate and vigorous exercise. Thus, it may meet the exercise requirements of both men and women.

Effect on Sustained Use

According to the habit theory, individuals' internal dispositions may become the main driving force to build a habit (Bargh et al. 2001). Thus, the diverse explicit motivations may lead to an initial action, the following actions may direct by the users' implicit motivations (Ouellette and Wood 1998). Although different explicit motivations may lead users to adopt different PA apps, the preference on PA apps may have stability under the effects of genders, which may serve as an implicit motivation. Thus, we suggest that the adoption of apps without a clear cognition on the motivation of themselves may lead to poor engagement performance. We hypothesize that:

H2. The preference in the PA app type has a positive impact on users' sustained use.

The past behavior on PA app is essential for habit formation process. On the one hand, the habits learning process is a repeated process. It requires information incremental in procedural memory in response to the repeated behavior (Pasupathy and Miller 2005). On the other hand, the engagement in the past behavior indicates the strength of self-regulatory sources (Ouellette and Wood 1998). These sources are essential for users to against the old, stable behaviors (Muraven and Baumeister 2000). Therefore, we propose that:

H3. Past behavior has a positive impact on users' sustained use.

Method

Data Description

The mobile data used in this study are from one of the three major mobile carriers in China. We make a PA apps list (14 apps included) based on the physical activity top-rank on three major application marketplaces in China: Apple iTunes (iPhone operating system), Ying Yong Bao (an Android application platform of Tencent Inc.), and Wan Dou Jia (Android APP platform of Zhuo Yi Xun Chang Technology Co., Ltd.). We randomly select samples from 700,000 users if they used only one PA app of our list from April 21st to May 20th, 2018. Totally, we obtain 10,263 samples, among which 6,559 are males and 3,704 are females. The average age of the samples is 37.09.

The raw data include individual's encrypted ID, age, gender, and app use logs. The logs record timestamps, location, and service information, which can tell where and when user use which app. These logs used to calculate phone bills by mobile carriers, including too much redundant information that cannot be directly analyzed. Thus, we filter the use logs and only extract PA app use logs. These processes are conducted under the Big-data framework with Hadoop and MapReduce (Dean & Ghemawat, 2008; Taylor, 2010).

The app definition and comments data are crawled from Wan Dou Jia. The platform marks every physical activity app, including the fitness/training app, the diet/caloric app, and the distance tracking app. We use these labels as the target exercise of apps and the comments as users' exercise purpose.

App Type Identification

We classify the PA app used in this study into three categories: fitness/ training, diet/ caloric intake, and distance tracking, drawing on the definition of Sama et al. (2014) and McGloin et al. (2017). These three categories of apps in Chinese application marketplaces account for a large proportion. Besides the function definitions of these apps, many commercial apps provide multiple functions to satisfied users' requirements. For instance, KEEP is defined as a fitness app, but it also provides a diet plan. It is necessary to distinguish whether users exercise purposes are consistent with the app main target exercise.

Since the identity information of our samples is encrypted, it is impossible for us to contact users and obtain the exercise motivations of these samples. Thus, we rely on the app comments to extract the exact exercise purpose of users. The comments of each app include the evaluation of the app, the difficulty when using the app, the recommendation, the use purpose, the performance of the exercise, and any other context they want to share with others. The comments platform is open access for all app users. It is reasonable to assume that the exercise purpose derived from these comments can represent all the users.

In this study, we use the Latent Semantic Analysis (LSA) to identify the similarity between app comments and the specific exercise (Landauer et al. 1998). LSA is a natural language processing method that can be used to analyze the relationship between a set of documents and the terms. Specifically, we develop three exercise corpus (fitness/training, diet/caloric intake, and distance tracking) based on the introduction of apps, where these apps are defined in the same exercise category at first. Then, we use the LSA to calculate the similarity value among exercise corpus and app comments. The exercise with maximum value can be recognized as the app type that the user uses them in real-world conditions.

Variable Definition

Before further analysis, we clarify the definition of the variable used in this study, as shown in Table 1. In order to isolate the correlation between independent variables and dependent variables, we extracted these two types of variables from the separated time intervals. The independent variables were calculated from the app use data in the first week and the dependent variables were extracted from the following three-week app use data.

For independent variables, app type preference are distinguished according to the gender preference examination results. The past behavior is adapted from the concept definition in Ouellette and Wood (1998).

For dependent variables, previous studies measure the sustained use of physical activity app mainly from four perspectives: intention to continue using physical activity apps (Canhoto and Arp 2017; Ehlers and Huberty 2014; Lee and Cho 2017), length of time using app (Serrano et al. 2017), time to inactivity or dropout (Du et al. 2016; Fukuoka et al. 2015), and non-usage attrition (the length of time that have no usage record) (Guertler et al. 2015). Since all the users are anonymity, we cannot contact users and ask them their intention to continue using the app. And limited by the time span and the complex of usage behaviors in practice, using the length of time to represent the sustained app use may not accurate. Therefore, we adapted the last two sustained use measurements as the dependent variables. Specifically, these two variables are (1) whether the average number of days in the last three weeks is more than two days (activity or inactivity), and (2) the maximum continuous days without app logs during the last three weeks.

Table 1. Description of variables used in this paper

Variable	Variable description
Independent Variables	
App type preference	Whether the PA app type is consistent with their gender preference
Past behavior	Number of days with app engagement records in the first week
Dependent Variables	
Sign of sustained use	Whether the average number of days in the last three weeks is more than two days
Non-sustained use time	The maximum continuous days without app logs during the last three weeks
Control Variables	Age, gender

Table 2 presents the descriptive statistics of samples and main variables.

Table 2. Descriptive Statistics of Variables

Variable	Mean/Number	Min	Max	SD
Gender	Female: 3,704 (36.09%)			
Age	37.09	16	86	11.387
App type preference	8,207			
Sign of sustained use	8,284			
Non-sustained use time	3.43	0	21	2.806
Observation	10,263			

Experiments and Results

App Type Identification

In order to test the consistency between the target exercise of apps and the exercise purpose of individuals, the LSA method is used to calculate their similarity. As shown in Figure 2, the first two apps are diet/caloric apps, the next three belong to fitness/training apps, and the last nine apps belong to distance tracking apps. For each app, the similarity between comments of each app and three exercise corpus is calculated respectively. The results show that most users adopt the PA app as the defined main target purpose. It is also reasonable because the app often provide more service for the main target exercise. Therefore, we can regard the label of the app as the app type.

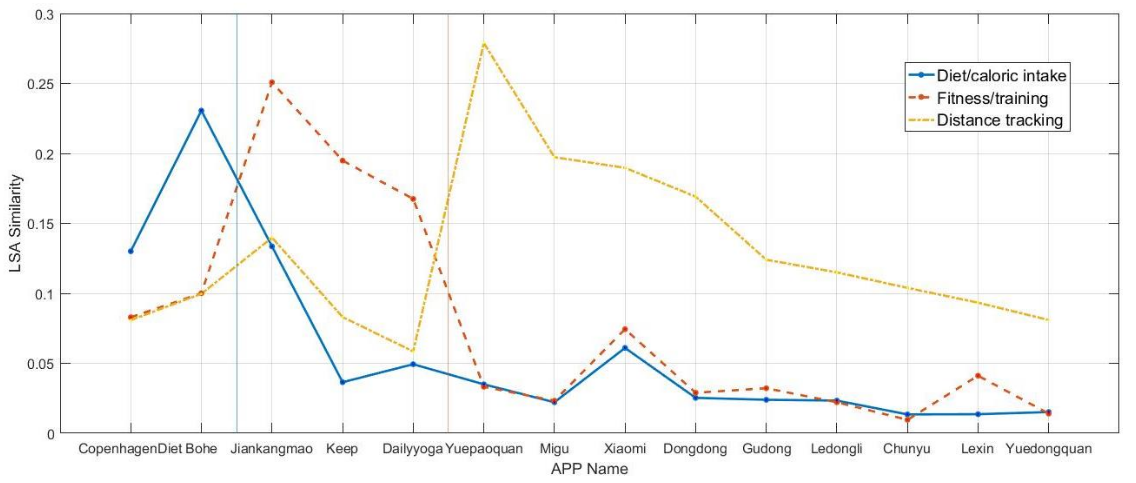

Figure 2. The Similarity Between App Types and App Comments

Gender Differences in PA app Type Preference

In order to test different preference to PA app types, the Cramer's V is employed to test the significance (McHugh, 2013). As shown in Table 3, the app type preference differences are significant in different genders (0.161, p-value<0.001).

Table 3. The Correlation Between Gender and the PA App

	Distribution	Fitness/ training	Diet/ caloric intake	Distance tracking	Cramer's V	*p-value*	Hypothesis
Male	6,559	15.7%	0.9%	83.4%	0.161	0.000 (<0.001)	H1a, H1b supported
Female	3,704	26.1%	3.5%	70.4%			

Results show that females are more likely to use diet/caloric intake and fitness/training apps (diet/caloric intake: 3.5% versus 0.9%; fitness/training: 26.1% versus 15.7% for female and male, respectively), supporting H1a and H1b. For the most popular app, the distance tracking apps, there are more male users than female users (83.4% versus 70.4% for men and women). For distance tracking apps, users can improve the running exercise from the services. The communal gender role indicates that males generally emphasize instrumentality and independence (Meyers - Levy and Loken 2015). Males are more likely to conduct actions that benefit themselves (Buchan et al. 2008). It is reasonable that men may be more likely to adopt these apps. Since the distance app users take up a large proportion, we do not differentiate the preferences by gender.

Effect on App Sustained Use

In order to examine the effect of app type preference and the past behavior on app sustained use, we develop two regression models respectively. Among them, the logistic regression is for the sign of sustained use (binary-valued variable), and the linear regression model is for the sustained use time (continuous variable). The results are shown in Table 4. We observe that both the two independent variables are significant, supporting H2 and H3. Notably, although the signs of coefficients on the two models are opposite, the meaning of the relationship in the two models are the same. The more preference for the app type and the more engagement in the past, the more likely the user maintain sustained use and have less interval between two use records. These findings suggest that long-term app usage is consistent with the habit formation process, that the repeated behavior and the suitable direction of activity are necessary (Wood et al. 2016).

Table 4. The Regression Analysis for Sustained Use

	Model 1 (Sign of sustained use)	Model 2 (Non-sustained use time)
Age	0.038***	-0.056***
Gender	-0.029**	0.023*
App type preference	0.023*	-0.031**
Past behavior	0.465***	-0.405***
Observation	10,263	10.263
R-Square	0.223	0.173

* p-value < 0.05 ** p-value < 0.01 *** p-value < 0.001

Discussion and Conclusion

PA apps have been widely used for health behaviors intervention. Prior studies mainly focus on the effectiveness and the influences on the adoption of the apps. However, these studies rare considerate users could choose different apps and the low retention rate issue in real-world conditions. In this study, we analyze the sustained use of PA apps from the habit formation perspective and test hypotheses using real data. The current study contributes to the literature in two ways. First, this study analyzes the app type preferences among different genders, which promote the understanding of individual adoption preference from the many PA apps. Second, under the guidance of habit theory, we construct a theoretical framework to explain the discontinued use of PA apps with use the app type preference and past behavior as predictors. This expands the understanding of PA app engagement and provides new insights on the behavior intervention direction.

In practice, our study can support to optimize the development of PA apps for several reasons. First, this study supports PA app designers to find their target users and provide special services for them. As our findings show, different genders prefer different app types, if the app can provide different services to satisfy requirements from different genders, they may promote users to use longer. Second, as the results indicate, the engagement is essential for sustained use. App designers can increase more services to stimulate users' to frequent use.

This study has several limitations that we will address in the future. First, the analysis is limited by the collected data, that we could not analyze the effect on longer duration. The future study should collect data with a longer period and use a more efficient method to address this issue. Second, since the data have limited details on the user themselves, this may cause the selection bias. More details data about users should be collected in future study. Additionally, since all the users are anonymous that we cannot verify our assumption. The survey or interview to verify the explanation of the phenomenon should be conducted in the future.

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