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Understanding People's Switching Intentions of Health Apps from Exterior and Interior Drivers

從外部和內部驅動力理解人們對於健康應用程式的轉換意圖

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Abstract

Health apps are one important type of apps that are designed to assist users with recording their health-related behaviors and giving advice to improve their physical condition. However, health apps users typically face a potential dilemma of keeping on using current apps or switching to others. This study conducts an empirical investigation and proposes an exterior-interior factor model based on Push-Pull-Mooring (PPM) model to figure out why users want to switch from the current health app to another new one. Specifically, positive drivers (exterior power) and negative drivers (interior power) are proposed in the research model to investigate switching intentions for health apps. The former includes attractive alternatives, social influence, and dissatisfaction with the current health app; the latter includes procedural switching costs and habits. To explore the determinants, this study conducts a survey and collects 218 qualified responses to serve as our research samples. We then exploit structural equation modeling (SEM) to analyze these samples. The result reveals that our research model explains 57% of the variance.

【Keywords】switching intention, health apps, exterior drivers, interior drivers

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摘 要

為了協助人們記錄自己的運動行為，和改善自己身體的健康情況，手機上所安裝或搭載的健康應用程式，是普遍會使用到的一種手機應用程式。然而，人們可能會因為一些潛在的原因而放棄或轉換健康應用程式。為了解哪些因素會影響人們轉換使用中的健康應用程式，本研究以人口遷移中的推力－拉力－維繫理論 (Push-Pull-Mooring Model, PPM) 為思考的基礎，提出外部驅動力與內部驅動力兩面因素的研究模式，試圖理解為何人們會考慮轉換目前使用的健康應用程式。本研究認為外部驅動力包括：替代品的吸引力、社會影響和不滿意現有應用；內部驅動力則包括：轉換成本和習慣。為驗證本研究模式是否具有解釋力，本研究共收集了 218 筆的有效問卷，並運用結構方程模式分析資料。研究分析結果顯示，我們的研究模式具有 57% 的變異解釋力。

【關鍵字】轉換意圖、健康應用程式、外部驅動力、內部驅動力

1. Introduction

In this decade, mobile technologies are of great importance in people's daily lives, and most people install their favorite applications (apps) on mobile devices, such as cell phones or tablets. To make a profit, app companies have developed various types of apps such as game apps, calculation apps, picture apps, social media apps, etc. for users to utilize in their lives. These apps all play important roles for users according to their various functions. In addition to the aforementioned apps, health apps are becoming more important for human beings (Xiong and Zuo, 2023). According to the definition of previous research, health apps are designed to provide some functions including tracking diets (weight change and dietary control) and improving nutrition, identifying symptoms (heartbeat, blood sugar and pressure), increasing physical activity (fitness support), and providing medication reminders, etc. (Cho, 2016; Chen, Yang, Zhang, and Yang, 2018; Xiong and Zuo, 2023). Health app may need to be downloaded and installed by the users, or it may be just one of the default mobile apps (Chen et al., 2018; Xiong and Zuo, 2023). IQVIA (2017) reported that "Over 318,000 health apps are now available on top app stores worldwide with more than 200 health apps being added each day."

Although health apps are useful and increasingly popular, studies have pointed out that users of health apps easily abandon their original apps and switch to new apps because they lose interest or feel that the apps are wasting their time (Vaghefi and Tulu, 2019). For example, Krebs and Duncan (2015) conduct an early survey of 1,604 mobile phone users in the United States and find that about half of the respondents (427/934, 45.7%) downloaded health apps before but are no longer using them. This study points out three superficial reasons for abandoning health apps, including: (1) lost interest (173/427, 40%), (2) did not help me as I wanted (81/427, 19%), and (3) found better apps (66/427, 15.5%). Likewise, Vaghefi and Tulu (2019) also find that for using of health apps, people often face four types of decisions, including: abandon use, limit use, switch apps, and continue use. They find that users may turn to other health apps if the initial health app doesn't meet their featural expectations. Based on these previous studies, we know that it is not uncommon for health apps users to make switching decisions. Meanwhile, most health apps are free and developers adopt freemium strategies or advertisements to earn enough profit to cover the development costs. However, if users switch from their original health apps to other counterparts, the developers no longer have opportunities to extract profits from users and receive no payback.

To deeply understand why people continuously switch between technologies, past information system (IS) studies have discussed the issue of switching intentions for IS and Information Technology (IT). For example, based on Unified Theory of Acceptance and Use of Technology (UTAUT), Bhattacherjee, Limayem, and Cheung (2012) develop and test a model of user IT switching behavior. The major determinants for IT switching behavior, according to their proposed model, are relative advantage, personal innovativeness, satisfaction with prior IT and habits. Fan and Suh (2014) conduct an empirical study based on Expectation-Disconfirmation Theory (EDT) to address why users switch to a disruptive technology. Their model considers not only the EDT but also two switching costs (financial and procedural) as the major factors to study the users' intention. Wong, Chang, and Yeh (2019) also propose a conceptual model which is based on the consumption value theory and the cognition affect behavior model for investigating smartphone brand switching behavior.

From the literature above, we know that the factors influencing switching intention/behavior of users may be fairly complicated. Users give up their current IS/IT (incumbent IS/IT) and turn to alternatives due to a multitude of considerations. Although past studies have explained users' switching IS/IT from the variables of expectation, dissatisfaction, disconfirmation (Bhattacherjee et al., 2012; Fan and Suh, 2014; Hou and Shiau, 2020), benefit/value (Wong et al., 2019) and task-technology fit theory (Chen and Koufaris, 2020), few studies use a push-pull concept (such as exterior-interior drives) to point out that users' IS/IT switching stems from a particular dilemma (Hou and Shiau, 2020). In addition, although past researches are also focused on analyzing the IS/IT switching problem in the use of hardware or software, such as web browser (Bhattacherjee et al., 2012), mobile devices (Fan and Suh, 2014), or social networking sites (Sun, Liu, Chen, Wu, Shen, and Zhang, 2017; Hou and Shiau, 2020); however, few studies have focused on switching issues of mobile apps with a large number of users. Particularly, different from traditional IS/IT, there are many candidates for users to replace their current health apps (Chong, Blut, and Zheng, 2022). Therefore, we believe there is a research need for understanding what drive users to switch health apps.

In order to fill the research gap, we conduct empirical research and propose an exterior-interior factor model to figure out why users want to switch from their current health app to other new ones. We believe that on the one hand, users may be positively motivated to switch their current app; on the other hand, they may be deterred from selecting other new apps due to certain factors. The result of the trade-off between the two powers is eventually determined by which power is larger than the other. Thus, we apply positive drivers (exterior power) and negative drivers (interior power) in this model to investigate switching intentions for health apps. By referring to variables proposed in past research (Bhattacherjee et al., 2012; Fan and Suh, 2014; Hou and Shiau, 2020; Wong et al., 2019; Chong et al., 2022; Nugroho and Wang, 2023), we select five variables that are consistent with the idea of external and internal driving forces. The former includes *attractive alternatives*, *social influence*, and *dissatisfaction* with the current health app; the latter includes *procedural switching costs* and *habits*.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 proposes the research model and hypotheses. Section 4 introduces the research methodology. Section 5 presents the findings of the analysis of the empirical data. Section 6 presents the contributions, implications, and limitations, and makes recommendations for future researchers.

2. Literature Review

The framework of our research model can be divided into two parts, positive drivers (exterior power) and negative drivers (interior power). The variables in the exterior are the positive effects on switching intention, while the variables in the interior are the negative effects on switching intention. The idea of the research model stems from the push–pull–mooring (PPM) population migration model (see Figure 1), which has been used to illustrate the effects of migratory migrants' intentional behavior (Lee, 1966; Bogue, 1969; Cohen, 1996; Bansal, Taylor, and St. James, 2005; Nugroho and Wang, 2023). We argue that push effects create a positive power to arouse users' intention to switch health apps, whereas pull effect forms a negative power to hold users who keep on staying with their current health apps. In accordance with the argument, this study selects five determinants *attractive alternatives*, *social influence*, *(dis)satisfaction*, *switching costs*, and *habits* from the related research in the past (Bhattacherjee et al., 2012; Fan and Suh, 2014; Lee, Han, and Jo, 2017; Hou and Shiau, 2020; Wong et al., 2019; Yan, Filieri, Raguseo, and Gorton, 2021; Chong et al., 2022). We also list the variables used in aforementioned past research in Table 1. Some past study has more variables due to combining different research models. In this study, because we specifically consider that the dilemma of switching health apps with individuals may present two forces (i.e. push and pull) that influence users' switching intentions, we treat *attractive alternatives*, *social influence*, and *dissatisfaction* as push power (exterior power); *switching costs* and *habits* as pull power (interior power). The following sub-sections describe the concept of selected variables.

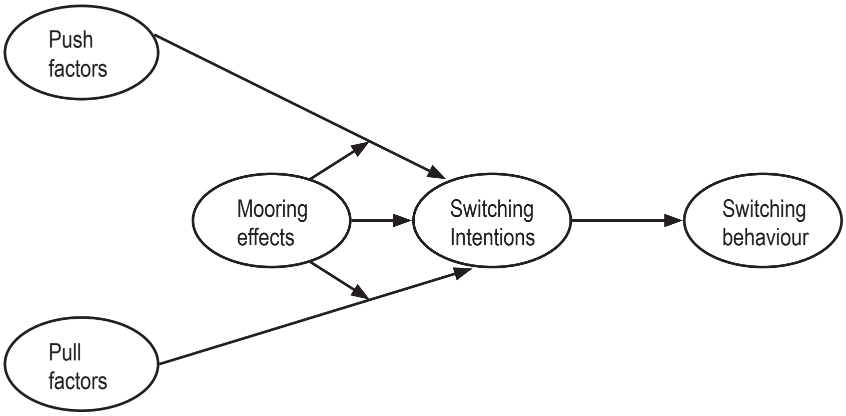

Figure 1 Push-Pull-Mooring (PPM) Model of Service Switching (Bansal et al., 2005)

2.1 Attractive Alternative

Alternatives refer to the existence of competing relationships between/among two/two or more products. In the marketing domain, alternative products refer to products with the same basic use. Yet alternative products also represent an increase in sales of one product while reducing the potential sales of other products. Determining an alternative is a value evaluation and primarily a matter of the alternatives offering greater value than existing products. Keaveney (1995) finds that when customers have switching intentions or behaviors, they are not necessarily dissatisfied with the original service providers; perhaps they are aware that other service providers offer more favorable traits, more rewards, or added value to attract customers, thus causing customers to produce this kind of intention or behavior. That is, when consumers perceive other alternatives offering more attractive solutions, they are attracted and may choose to partner with the vendor. Conversely, if the

Table 1 The Variables Used in Past Research

Study	Research Variables	Theory/Model	Technology
Bhattacherjee et al. (2012)	*Relative advantage, Satisfaction with prior IT, Personal innovativeness, Habit*	UTAUT	Web browser
Fan and Suh (2014)	*Dissatisfaction, Disconfirmation, Expectation, Financial switching cost, Procedural switching cost*	Expectation-Disconfirmation Theory (EDT)	Mobile devices
Lee et al. (2017)	*Health stress, Epistemic value, Usefulness, Enjoyment, Convenience, Reassurance*	Context/Contents Values Model	mHealth Apps
Hou and Shiau (2020)	*Socializing, Enjoyment, System quality, Satisfaction, Attractiveness of the alternative, Peer influence, Critical mass*	Push-Pull Mooring Model (PPM)	Social networking sites
Wong et al. (2019)	*Functional value, Emotional value, Social value, Epistemic value, Functional benefit, Social benefit, Confidence benefit, Special treatment benefit*	The Consumption Value Theory	Smartphone
Chong et al. (2022)	*Anxiety, Attitude, Effort expectancy, Enjoyment, Facilitating conditions, Habit, Image, Task relevance, Output quality, Performance expectancy, Result demonstrability, Self-efficacy, Social norms, Usage behavior, Usage intention, Value*	TAM, UTAUT	Healthcare information technologies

original manufacturer is able to provide more attractive solutions, customers will stay with the original manufacturer (Wathne, Biong, and Heide, 2001). In addition, Keaveney (1995) refers to the factors behind switching between competitors as “competitive issues.” It can be seen that in a competitive environment, even when customers have high satisfaction, it may still lead to a high willingness to change in the face of attractive promotional programs or more attractive services or quality. Such willingness to change may occur particularly when competition between businesses is fierce. Therefore, industry players apply various marketing tools to attract customers’ attention, such as customized pages, design hierarchy, community competition or rewards, etc. The above marketing methods show that in order to retain customers in a highly competitive environment, it may be necessary to increase customer barriers to lock-in customers and think about how to prevent other attractive alternatives.

2.2 Social Influence

Social influence refers to the way in which individuals change their behavior to meet the demands of a social environment (Cialdini and Goldstein, 2004). Past literature has also pointed out that individuals are influenced by the information, norms, and values of others in response to what they perceive others might do or think (Darley and Latané, 1970; Rice, Grant, Schmitz, and Torobin, 1990). As a result, the longer an individual receives messages from others, the more likely it is that the individual's behaviors and decisions will be affected (Deutsch and Gerard, 1955; Ajzen and Fishbein, 1980), and may also change individual perceptions through such processes (Wang, Meister, and Gray, 2013).

In the research of technology adoption, Venkatesh, Morris, Davis, and Davis (2003) state that social impact refers to the extent to which individuals feel that important others can influence their use of a new system. For example, many game apps in mobile devices have started to develop various social interaction functions so that social influence becomes very important. Users of the game apps can see the rankings and achievements of their friends, or form groups, and then share feelings that affect community members. The commitment and willingness to share knowledge can certainly reflect the social impact of users (Huang, Chen, and Liu, 2019).

2.3 Customer Satisfaction

Customer satisfaction is a state of pleasure or disappointment that is formed by consumers after the perceived effect of a product is compared to the expectation (Kolter, 1996). Early scholars, such as Cardozo (1965), believe that customer satisfaction is an indicator of repeat product purchases. Thus, scholars have suggested that the satisfaction of product attribute performance should be measured. However, the measurement of customer satisfaction from the target customers of different industries varies. For example, Woodside, Frey, and Daly (1989) point out that customer satisfaction is the attitude that customers evaluate after they purchase or use the product. Kim and Yoon (2004), in a study of the Korean mobile phone industry, mention that the measurement of customer satisfaction can be classified as call quality, ringtones, customer service, mobile phone appearance, and other items. In addition, Deng, Lu, Wei, and Zhang (2010) research into customer satisfaction of mobile instant messages, the research factors include trust, service quality, social value, perceived value, etc. Using these factors, their study aims to figure out the degree of customer satisfaction. The results show that the above four factors have obvious impacts on customer satisfaction. Based on the finding of Deng et al. (2010), this study employs dissatisfaction as a variable to explore whether it can influence switching intentions for health apps. Dissatisfaction is the reverse sentiment of satisfaction; therefore, we substitute the instrument of dissatisfaction for that of satisfaction.

2.4 Switching Costs

Dick and Basu (1994) and de Ruyter, Wetzels, and Bloemer (1998) suggest that the switching cost is the cost of alternating from one service provider to another. In addition to the financial cost, consumers still have to face the time spent or psychological uncertainty brought by changing to a new provider. In the field of marketing, Jones, Mothersbaugh, and Beatty (2000) point out that switching costs are consumers' perceived costs in switching vendors, such as finance and time. This cost would not be incurred if the user retains the original supplier. When the switching cost is high, the customer is forced to continue trading with the existing supplier; that is, the willingness to switch decreases. When considering switching suppliers, customers assess whether the cost of the switch is greater than the cost of staying at the existing supplier. In addition, Burnham, Frels, and Mahajan (2003) explore the types of switching costs, divided switching costs into three following categories:

(1) Procedural switching costs mainly refer to the customer's time and effort;
(2) Financial switching costs mainly refer to the loss of customer-measured financial resources;
(3) Relational switching costs mainly refer to the emotional or psychological loss of the customer.

This study focuses on switching of health apps. When users are going to switch their current app, they must face new procedural settings, learning, uncertainty and take risk when using a new alternative. Therefore, we mainly use the procedural switching cost as a variable to further explore switching costs. Since health apps are similar in function and are nearly free to download and use, the financial switching costs and relational switching costs are not considered in this study.

2.5 Habits

Habits are identified as "learned sequences of acts that have become automatic responses to specific situations and are functional in obtaining certain goals or end-stated" (Verplanken and Aarts, 1999). Most peoples' actions are based on a foundation of convention. Habits can be considered as psychological temperaments meant to duplicate past behavior. With recurring behavior, people gradually react to this kind of repetitive behavior (Wood and Neal, 2007, 2009). Most researchers believe that habits are usually derived from the pursuit of goals, because people may repeat actions which are beneficial to them or produce expected results (Ouellette and Wood, 1998; Colgate and Danaher, 2000; Gefen, 2003).

In the field of management information systems (MIS), IS habit is primarily an automatic behavioral tendency due to satisfaction and previous frequency of use. User satisfaction may increase because a certain behavior is performed frequently. In addition, IS habit has evolved over time and is often embedded in higher-level work for larger and frequently practiced routines or tasks (Polites and Karahanna, 2012). However, existing IS practices embedded in these routines can hinder the adoption and use of new systems when new systems are introduced to replace existing systems. Consequently, according to the above discussion, this study explores whether habits can negatively affect users' switching intention.

2.6 Switching Intention

Switching intention refers to the desire to leave a relationship or the degree of intention to terminate a partnership (Ping, 1993). Keaveney (1995) is one of the early scholars who studies the switching intentions of customers in the service industry. In the results of a critical incident study conducted in over 500 service customers, more than 800 reasons are found to reveal why customers want to switch services. Switching intention mainly comes from the evaluation results after the consumer uses a product or service (Keaveney, 1995). There are two evaluation methods: (1) satisfaction with the product, i.e., when the satisfaction is high, the willingness to accept the service is enhanced; (2) relative ratio assessment, i.e., when the consumer believes that the current brand is not as good as other brands, switching intention increases. Following the study of Keaveney (1995), many studies have been conducting surveys of customers' switching behaviors in various industries, including auto services and mobile phone providers. In this study, we also refer to the definition of Keaveney (1995) and focus on examining the determinants related to switching intentions of health apps.

3. Research Model and Hypotheses

3.1 Theoretical Foundation

The PPM model is one of the most important and common theories used to interpret human migration behavior (Lee, 1966; Bogue, 1969; Cohen, 1996). This model considers human migration as the result of the interaction between "the thrust of the original residence place and the pull of the destination" (Hou, Chern, Chen, and Chen, 2011; Sun et al., 2017); some effects of the original place encourage the individual to leave, while the effects of the new place of residence appeal to individuals (Lewis, 1982). Furthermore, Longino (1992) proposes the concept of "mooring" to describe the long-term, cumulative resources of migrants in their original residences and their impact on migration decisions (Chen, Shang, and Li, 2014). Moon (1995) incorporates the mooring force into the PPM model and points out that mooring power includes an individual's life course and cultural and spatial issues. These issues motivate or prevent and individual's migration decisions, including all personal, social, and cultural effects (Moon, 1995).

Bansal et al. (2005) propose the theoretical framework of the PPM model for marketing research and find that the PPM model can be applied to investigate the switching of consumers between service providers; thrust, pull, push, and mooring significantly affect the consumer's intention to switch a service provider. Hou et al. (2011), Sun et al. (2017), and Nugroho and Wang (2023) also use the PPM model to study the switching intentions of E-services, such as online games, instant messengers, and online to offline (O2O) purchasing. They validate their research model with different variables and find that PPM model has explanatory power for users' decision to switch E-services. Based on the PPM model and the results of past relevant studies, we propose a research model and the following hypotheses to understand switching intentions of health apps. Figure 2 illustrates the research model.

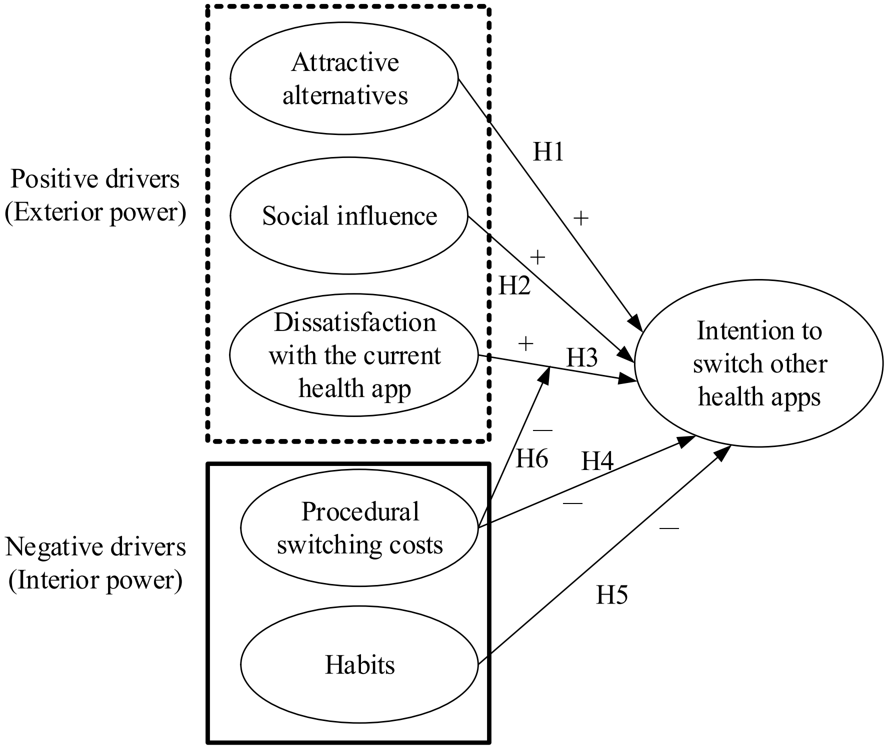

Figure 2 Research Model

3.2 Hypotheses

Ping (1993) argues that attractive alternatives positively impact customers' switch intentions; Dwyer, Schurr, and Oh (1987) state that alternatives positively affect customers' switch intentions when overall satisfaction is low. In the context of health apps, users may not change their usage behaviors even if they are dissatisfied or unpleased with the current app when they understand that there is a lack of alternatives or the benefits are not higher after switching. Conversely, when the alternatives are more attractive and functional, consumers may switch from the current app to other products. Therefore, this study suggests that when there are more attractive alternatives, consumers' willingness to change increases. Thus, we propose the following hypothesis:

Hypothesis 1 (H1): Attractive alternatives have a positive effect on the intention to switch to other health apps.

An app is an experiential product and it is difficult to judge its value before using it. In this kind of situation, consumers tend to collect more product information, especially through user evaluation, to determine whether the product is worth using (Chen et al., 2014; Jeong and Jang, 2011). One approach to user evaluation is to refer to actual experiences of other users who have experienced the apps (Mathieson, 1991). These experienced users are able to leave their comments about the apps and have social influence on new users. Products (apps) with higher social influence will positively influence consumers' choices; thus, this indicates that consumers are influenced by the power of social influence to evaluate whether they are going to continue using an app or switch to another one (Huang and Chen, 2006). Therefore, if users know that a new app is highly positively rated by other experienced users, implying high social influence, the intention to switch to other apps might be enhanced. In accordance with the above argument, we propose the following hypothesis:

Hypothesis 2 (H2): Social influence has a positive effect on the intention to switch to other health apps.

Many studies have focused on consumer satisfaction with mobile devices (Liao, Liu, Liu, To, and Lin, 2011). Most of the results show that customer satisfaction is positively correlated with behavioral intentions (Wirtz, Xiao, Chiang, and Malhotra, 2014). For example, Gerpott, Rams, and Schindler (2001) conduct a study of the German mobile phone market, and their results show that customer switching intention is impacted by satisfaction and dissatisfaction. Su and Cheng (2016) explore the satisfaction measurement of the Nike+ Running App. They discuss four aspects of app (i.e., technology, app information quality, app service ability, and app interface design) to explore the willingness of customers to continue using the product. The preliminary result shows that customer satisfaction leads to continued use of the product, and dissatisfaction results in customers' switching to another product. In a similar vein, we explore the switching factors related to health apps. Based on the above discussion, dissatisfaction causes customers to change products, so the following hypothesis is proposed:

Hypothesis 3 (H3): Dissatisfaction with current health app has a positive effect on the intention to switch to other health apps.

Switching costs are subjective, emotional, and difficult to assess (Weiss and Anderson, 1992). Past studies have showed that consumers estimate the benefits when they intend to change suppliers. If consumers think that the cost is higher than the benefit they will receive, they will not change (Jones et al., 2000). Therefore, the ultimate effect of switching costs is to encourage customers to maintain relationships with current suppliers. Hu and Hwang (2006) point out that the increase of the procedural switching cost and the relationship of switching cost significantly reduce the willingness to switch in their study of the mobile communication industry. In addition, Burnham et al., (2003) learn that the higher the switching cost perceived by consumers, the higher the willingness to continue to cooperate with the original supplier in the credit card and long-distance communication industries. Considering the relationship between switching cost and intention, we propose that:

Hypothesis 4 (H4): Procedural switching costs have a negative effect on the intention to switch to other health apps.

Habits affect continuous use behavior when using health apps. When users' behaviors turn into automatic responses and actions, they demonstrate cognitive economics and performance efficiency (Limayem, Hirt, and Cheung, 2007; Limayem and Cheung, 2011). Users rely more on habits than on using external information for strategic use (Gefen, 2003). Colgate and Danaher (2000) point out that habitual behavior is the foundation of human nature. As customers get used to specific things, there is no strong motivation to find alternatives; that is, habits are developed in response to a person's past, leading to an automatic behavioral tendency. Since high-relational habit is a form of intuitive thinking, when consumer behavior does not require much thinking, the willingness to switch may be weakened. Accordingly, we propose the following hypothesis:

Hypothesis 5 (H5): Habits negatively influence the intention to switch to other health apps.

Since the effects of switching costs on switching intentions have been studied extensively, this study explores the moderating effect of the switching cost between dissatisfaction and switching intentions. A past study shows that consumers that are dissatisfied with the existing IT are likely to switch to other ITs (Bhattacherjee et al., 2012). However, considering the effect of switching costs, when consumers compare the benefits of switching or not switching, they sometimes lose their switching intention. This is because the switching costs may exceed the consumer's expectations about new IT. IT switching is considered a risky behavior and the results are often unpredictable. Therefore, consumers who are afraid of taking risks and are cost sensitive may be reluctant to switch to new IT even though they are slightly dissatisfied with the existing IT. Based on the argument above, if a health app is considered an IT, in the context of this study, switching cost may be expected to weaken the positive impact of dissatisfaction on the intention to switch to a new health app. Thus, we propose the following hypothesis:

Hypothesis 6 (H6): Procedural switching cost has a negative moderating effect on dissatisfaction with the current health app.

4. Research Methodology

4.1 Questionnaire Development

In order to test our research model, we conduct a survey including items for each of the constructs. We adopt existing validated scales from the well-established and reliable research instruments and turn into a three-part questionnaire. The first part is a detailed description of the purpose of this study to ensure that respondents have used health applications (apps). The second part includes the items for each of the constructs measured by a seven-point Likert scale. The last part is the nominal scale, collecting the basic information of the respondents and the control variables of the research model. The Appendix shows the questionnaire of second part.

4.1.1 Item Development

To ensure the validity of the research content, we rewrite and develop each structured survey item from previous research to fit the health app research environment, as shown in the Appendix. We measure each item with a seven-point Likert scale, with 1 being "very disagree" and 7 being "very agree". Since both research conducting and data collection are in Taiwan, we translate the original questionnaire from English into Chinese. To ensure the quality of the translation, we review the Chinese and English versions and conduct a pilot study with faculties, doctoral students, and graduate students. The feedback from the pilot study leads to modifications of the measurements to improve the questionnaire, including the clarity, wording, sequence of items, and statements. We then launch the main study after these modifications.

4.1.2 Basic Information

This section collects basic information about respondents, including gender, age, education, occupation, mobile device operating system, the number of health apps in his/her mobile device, the year in which the health app is used, and the number of times the health app was used in the last month. Some of these features are considered as control variables, such as gender, age, and application experience.

4.2 Study Design and Procedure

The purpose of this study is to explore users' switching intentions of health apps. This research examines health apps like Apple Health, Google Fit, Fitbit, MyFitnessPal, etc. These apps are designed to record users' physical condition and thus lead to healthier condition. To collect the questionnaire data, we adopt an online survey methodology for the following reasons: First, it breaks geographical restrictions; second, it allows an unlimited number of respondents; last, it costs less and response is quick (Denscombe, 2006). Therefore, we test the research model by collecting online survey data. Using a perceptual experience method, we ask respondents to recall health apps they used in the previous month, ensuring that respondents have a clear memory when they answer the questionnaire. We publicly release the online survey on the health life board of PTT bulletin board system and healthcare groups of Facebook; we conduct the survey from February to March 2019. In the online questionnaire, we design a self-screening question at the beginning of the questionnaire: "Are you currently "using" a health app; if not, please do not fill up this questionnaire and skip it, thank you." Therefore, we can recruit the qualified participants.

Furthermore, we establish an award system to attract more respondents and drive them to respond to the survey seriously. The procedure of the reward system is to request the qualified participants to leave their email addresses so that we could create a list of qualified participants. Once we finish the data collection, we randomly sample 10 qualified participants from the pool and reward them the gift card (worth 3.3 US dollars). We believe that such a system made our study more successful than previous studies which have placed surveys on an online platform without any compensations.

Through the procedure of the questionnaire survey, we collect the data of 228 participants. After removing unqualified subjects who had no experience using health apps but still filled out the questionnaire, 218 subjects are eligible for data analysis. Table 2 shows the detailed demographic characteristics of the eligible participants. The gender distribution of participants is 33% men and 67% women. As for age, most participants (60.8%) are about 20 to 29 years old. In addition, most participants have received higher education; 40.1% of participants are college students, and 40.6% are master's students or above. The most popular health apps used are Apple Health (59.6%), followed by Samsung Health (11%), Google Fit (9.6%), and MyFitnessPal (5.5%). Most participants start using the health apps within the last 3 years (93.5%); consequently, we can observe that the use of health apps has gradually become a trend in recent years. However, most participants use the health apps infrequently; 86.2% of participants indicate that their total usage in the last month is less than 10 hours, and 77.5% of participants say they used the apps less than ten times in the last month. Generally speaking, we believe that this information will help suppliers to understand more about what users are thinking.

5. Data Analysis and Results

This study analyzes the data collected from the questionnaire by using statistical software SPSS 22.0 and partial least squares (PLS), which are analytical tools to validate the research hypotheses. This study also applies structural equation modeling (SEM), a statistical method combining factor analysis and path analysis. Among the methods of SEM, this study uses partial least squares (PLS), and many scholars have proved that the PLS method is one of the best methods for testing empirical SEM (Xu, Dinev, Smith, and Hart, 2011). In order to use PLS, the number of samples must meet their standards. The minimum sample size of PLS is ten times the number of indicators and is associated with the most complex or largest number of endogenous constructs (Marcoulides, 1998). The research model involves 6 constructs; therefore, the sample size of 218 meets the requirement of the PLS. We then use Smart-PLS 2.0.M3 to analyze data. This study also uses a two-step approach, provided by Anderson and Gerbing (1988), to analyze data collection for this survey. The first step is to check the measurement model and the second

Table 2 Demographic Characteristics of the Response Sample

Characteristics	Frequency	Percent (%)
Type of using health app		
Fitbit	6	2.8
Apple Health	130	59.6
Google Fit	21	9.6
HTC Sense companion	5	2.3
Huawei Health	3	1.4
MyFitnessPal	12	5.5
Samsung Health	24	11.0
iCare Health Monitor	2	0.9
Other	15	6.9
Gender		
Male	73	33
Female	145	67
Age		
<14 years of age	0	0
15-19 years of age	19	8.8
20-24 years of age	103	47
25-29 years of age	30	13.8
30-34 years of age	12	5.5
35-39 years of age	14	6.5
40-44 years of age	18	8.3
45-49 years of age	9	4.1
>50 years of age	13	6.0
Education level		
Primary	0	0
Junior high	1	0.5
Senior high	29	13.4
College	13	5.5
University	87	40.1
Graduate or above	88	40.6
Occupation		
Student	114	52.1
IT/Communication	6	2.8
Financial/Insurance	10	4.6
Technology/Science	7	3.2
Education	14	6.5
Government	5	2.3
Medical	5	2.3
Manufacture	14	6.5
Service	30	13.8
Nonprofit Organization	1	0.5
Retired	4	1.8
Other	8	3.7
Operation system of your mobile device		
iPhone OS	139	64.1
Android	73	33.2
Windows Mobile	6	2.8
Other	0	0
Own health app number		
1-2	204	93.6
3-4	12	5.5
≥5	2	0.9
Usage experience of health apps		
< 1 year	119	54.6
1-3 years	86	39.4
4-6 years	13	6.0
7-9 years	0	0
> 10 years	0	0
Total usage time in the last month		
<1 hour	98	44.5
1-10 hours	91	41.7
11-20 hours	14	6.4
21-30 hours	9	4.1
31-40 hours	2	0.9
41-50 hours	1	0.5
>51 hours	3	1.4
Frequency usage of the health app in the last 1 month		
0	40	18.3
1-5	96	43.6
6-10	34	15.6
11-15	16	7.3
16-20	12	5.5
21-25	9	4.1
26-30	7	3.2
>31	4	1.8

step is to check the structural model. We provide a detailed description of the two-step method as follows.

5.1 Analysis of the Measurement Model

This study uses confirmatory factor analysis to test the measurement model and study its reliability and validity. In PLS, it is generally recommended to use Cronbach's α, composite reliability (CR), and average variance extracted (AVE) to verify its reliability (Hair, Black, Babin, and Anderson, 2009). For the value of Cronbach's α, it is recommended that the test value should be above 0.7, indicating that the facet has good reliability (Nunnally, 1978). As for the value of CR, the recommended detection value should be above 0.7, indicating that its facet achieves internal consistency (Chin and Newsted, 1999; Chin, Marcolin, and Newsted, 2003). Besides, the AVE of each dimension should be greater than 0.5, indicating that each facet has sufficient convergence effectiveness (Fornell and Larcker, 1981). Table 3 shows that the reliability index results of all these dimensions meet the recommended standards.

In addition, in order to verify validity, we measure content validity and structural validity as well. Since the items of this study are derived from previous research, the content validity can be ensured. On the other hand, construct validity is often used to test discriminant validity. The PLS test discriminates the validity by placing the square root of the AVE of the individual dimension in the diagonal of the correlation coefficient matrix. In order to pass the test of discriminant validity, the square root of AVE should be greater than the correlation coefficient of the dimension and other dimension in the model (Chin, 1998; Chin et al., 2003). Table 4 shows the discriminant validity of all constructs, which fulfill the standards. The numbers on the diagonal are larger than the numbers under the diagonal, so it can be explained that all constructs have discriminant validity.

If the correlation coefficient is greater than 0.74, multiple-collinearity of the two variables is suspected. However, Table 4 shows that one of the correlation coefficients is higher than 0.74; thereby, the multiple-collinearity problem may exist, so we calculate the variance inflation factor (VIF), which can be used to determine whether there is a collinearity problem. We then use regression analysis to find the VIF value of each variable. VIF values range from 1.0 to 2.0, well below the recommended maximum level of 3.3-10.0 (Diamantopoulos and Siguaw, 2006; Hair et al., 2009). There are no VIF values

Table 3 The Reliability of the Measurement Model

Construct	Indicator	Factor Loading	Cronbach's Alpha	Composite Reliability (*CR*)	Average Variance Extracted (*AVE*)
AA	*AA1*	0.802	0.838	0.897	0.745
	AA2	0.881			
	AA3	0.904			
SI	*SI1*	0.920	0.937	0.960	0.888
	SI2	0.957			
	SI3	0.949			
DIS	*DIS1*	0.902	0.968	0.975	0.886
	DIS2	0.954			
	DIS3	0.958			
	DIS4	0.950			
	DIS5	0.941			
PSC	*PSC1*	0.842	0.934	0.951	0.828
	PSC2	0.935			
	PSC3	0.918			
	PSC4	0.942			
HAB	*HAB1*	0.813	0.872	0.914	0.781
	HAB2	0.904			
	HAB3	0.930			
IS	*IS1*	0.961	0.960	0.974	0.926
	IS2	0.955			
	IS3	0.971			

* Each parameter conforms to the recommended values recognized by the scholars
Factor Loading > 0.7
Cronbach's Alpha > 0.7
Composite Reliability > 0.7
Average Variance Extracted > 0.5

Table 4 Discriminant Validity

Construct	*AA*	*SI*	*DIS*	*PSC*	*HAB*	*IS*
AA	0.863					
SI	0.265	0.941				
DIS	0.207	-0.109	0.884			
PSC	0.272	0.746	-0.141	0.962		
HAB	0.181	0.385	0.160	0.291	0.910	
IS	0.356	0.558	0.091	0.587	0.387	0.942

* The square root of the *AVE* for each construct is greater than any other correlations between the construct and other constructs.

higher than this benchmark, indicating that our data has no obvious multiple-collinearity problem.

Lastly, we use Pearson correlation coefficient analysis to reflect the degree of close relationships between the variables. The higher the absolute value of the correlation coefficient between the two variables, the greater the mutual covariation. In general, when there is a positive correlation between the two variables, X and Y, then Y will increase as X increases; conversely, when there is a negative correlation between the two variables, then Y will decrease as X increases. We use SPSS 22.0 to find the Pearson correlation coefficients and their significance values. The results show that the correlation coefficient of *attractive alternative*s and attention to switch other health apps is 0.174, and the *p*-value is 0.031; therefore, the two variables achieve significant low correlation. *Social influence* and intention to switch to other health apps have a correlation coefficient of 0.502 and a *p*-value of 0; therefore, the two variables achieve a significant moderate correlation. *Dissatisfaction* with the current health app and intention to switch to other health apps have a correlation coefficient of 0.687 and a *p*-value of 0; therefore, both achieve a significant moderate correlation. *Procedural switching costs* and intention to switch to other health apps have a correlation coefficient of 0.212 and a *p*-value of 0.008; therefore, both achieve a significant low correlation. *Habits* and attention to switch to other health apps have a correlation coefficient of -0.318 and a *p*-value of 0; therefore, the two variables achieve a significant low correlation. The interaction effect between procedural switching costs and dissatisfaction with the current health app and intention to switch to other health apps have correlation coefficients and the *p*-value is 0. Procedural switching costs and intention to switch to other health apps have a correlation coefficient of 0.212, indicating a significant low correlation. Dissatisfaction with the current health app and intention to switch to other health apps have a correlation coefficient of 0.687, indicating a significant moderate correlation.

5.2 Analysis of the Structural Model

After testing the reliability and validity of each construct, this study has confirmed that each indicator has a certain degree of reliability and validity. Therefore, the substantive relationship between the various indicators can be further verified. We use PLS to check the structural model and estimate the structural model with path coefficients and

R^2 values. The path coefficient represents the direct effect, i.e., the strength and direction of the relationship between variables, and higher values have a greater effect. The R^2 value is the explanatory power of the structural model and can explain and predict the percentage of the independent variance of the relevant variance. In order to obtain the path coefficient and the R^2 value, this study first executes the PLS algorithm, and then executes the bootstrapping algorithm to check whether the path coefficient is significant. The t-value is demonstrated on the path. If the t-value is greater than 2.57, it means that the significant level is 1% ($p < 0.01$); if the t-value is greater than 1.96, it means that the significant level is 5% ($p < 0.05$), which is the commonly used standard (usually t-value being greater than 1.96 is called significant); if the t-value is greater than 1.65, it means that the significant level is 10% ($p < 0.1$), which is less obviously significant.

To evaluate the quality of the structural model, we also check the standardized root mean square residual (SRMR) of the structural model in order to evaluate the potential model misspecification issue (as shown in Table 5). The SRMR of our structural model is 0.053, which does not exceed the recommended cutoff value of 0.08. The value of normed-fit index (NFI) is 0.863, which is slightly less than the recommended standard value of model fit, 0.9; this NFI value suggests a good fit.

Table 5 Model Fit Analysis

	Saturated Model	Estimated Model
SRMR	0.053	0.053
d_ULS	0.66	0.66
d_G	0.486	0.484
Chi-Square	668.543	665.373
NFI	0.863	0.863

* The reference value of the estimated model as follows:
SRMR < 0.08
NFI > 0.9

For the setting of the number of bootstrapping samples, we refer to the advice provided by Hair, Ringle, and Sarstedt (2011) that the number of bootstrapping samples should be larger than the number of qualified samples. Since the number of bootstrapping samples is greater than 5,000, the result should be stable. We present the path coefficients, R^2 values, and statistical significance of the study model in Figure 3.

Overall, the model has 57% explanatory variation to account for the various

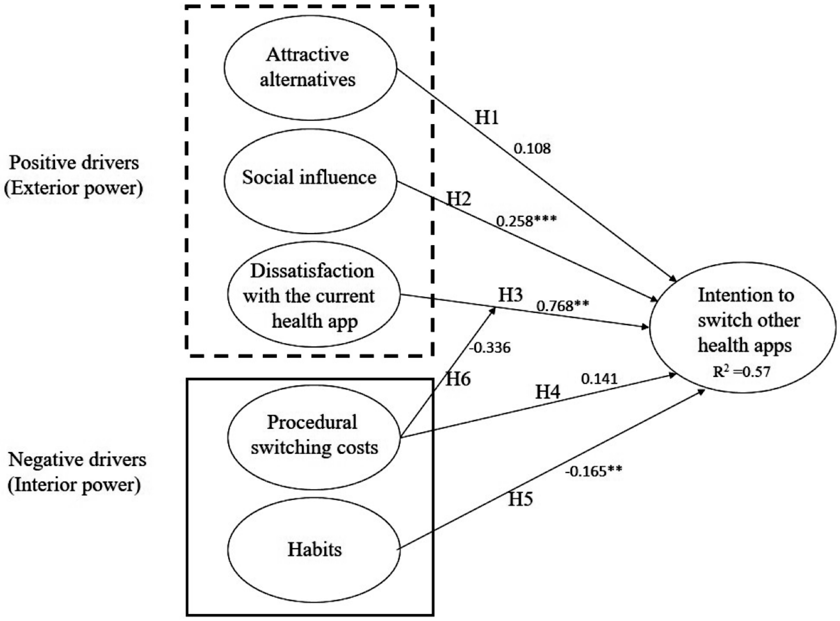

Figure 3 Results of the Research Model Analyses

Note: Value on Path: Standardized Coefficients (β); $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

determinants of switching intention, namely *social influence*, *dissatisfaction* with the current health app, and *habits*, with the path coefficients being 0.258, 0.768, and -0.165 ($\beta = 0.258$, $p < 0.001$; $\beta = 0.768$, $p < 0.01$; and $\beta = -0.165$, $p < 0.01$), respectively. Therefore, Hypotheses 2, 3, and 5 are significantly supported. In addition, *attractive alternatives* have a path coefficient of 0.108 ($\beta = 0.108$, $p > 0.05$) on the path; it is close to the minimum criterion of 1.96 for the significance criterion, showing only slight significance. Even so, Hypotheses 1 is not supported. Moreover, the path coefficient on the path of procedural switching costs is 0.141 ($\beta = 0.141$, $p > 0.05$), and the result is not significant, indicating that this independent variable has no effect on *the switching intention*; therefore, Hypothesis 4 is not supported. In addition, we can observe the effect of the moderator in the model. Hypothesis 6 assumes that *procedural switching cost* will have a negative moderating effect on *dissatisfaction* with the current incumbent health app, and the path coefficient is -0.336 ($\beta = -0.336$, $p > 0.05$). The result is not significant; therefore, Hypothesis 6 is not supported. To sum up, the overall explanation of variance to switch is 57.32%, and the analysis supports three hypotheses (H2,3,5) and does not support the other three hypotheses (H1,4,6). Corresponding to the analysis results, we provide the following reasons to explain why the users of health apps have switching intentions or are unwilling to switch to other apps in the following section.

5.3 Findings

In this study, we identify significant determinants of *user switching intention* and analyze the effects of positive drivers and negative drivers. The results show that *social influence*, *dissatisfaction* with the current health app, and *habits* have a relatively large impact on *user switching intention*. The above results indicate that the user's decision about whether to change to other apps is influenced by the evaluation of other users; the greater the *social influence*, the higher *the intention of the user to switch*. The significance of *social influence* is the greatest, so we can infer that in today's society, usage behavior is easily affected by friends and peers. In addition, when users are not satisfied with their current health app, they are easily attracted by other competitors' products and *user switching intention* is higher. Finally, *habits* make people feel dependent; if users get used to employing their current health app, the intention to use other apps is reduced.

However, *attractive alternatives* have no significant impact on *user switching intention* of health apps. The reason may be that most health apps are similar in functionality and almost free to begin with. Therefore, for users, there is almost no difference when compare between the old and new apps. In addition, *procedural switching cost* has also no significant impact on *user switching intention*; this indicates that health apps in the app market are always similar in their operational interface. Thus, *switching intention* is not reduced due to *procedural switching cost*. Also, *procedural switching cost* does not cause the user to change his/her current health app. In terms of interaction, we use *procedural switching cost* as a moderating variable to explore whether the variable leads users who are not satisfied with the original health app to switch to other providers. The result is not significant and indicates that *procedural switching cost* has no significant impact on the *user's switching intention*, even if the user is not satisfied with the existing health app.

To examine the robustness of the research model, we also analyze the moderating effect of *procedural switching cost* on *attractive alternatives* and *social influence* to test whether it has a significant impact on the switching intention. The results show that *procedural switching cost* has no significant moderating effect on *attractive alternatives* (β = -0.310, $p > 0.05$) and *social influence* (β = -0.052, $p > 0.05$). Besides, the path coefficients of *habits* on *attractive alternatives*, *social influence*, and *dissatisfaction* with the current health app are -0.166, -0.316, and -0.424. (β = -0.166, $p > 0.05$; β = -0.316, $p > 0.05$; and β = -0.424, $p > 0.05$), respectively. The results show that *habits* as a moderating variable is more influential than procedural switching cost, but it is still not significant.

6. Implications and Conclusion

6.1 Theoretical Implications

This research provides some novel and meaningful contributions to the literature. First, previous studies have examined the factors that affect users' IT/IS switching, such as Bhattacherjee et al. (2012) and Fan and Suh (2014). These studies separately identify several key factors, including relative advantage, satisfaction/dissatisfaction, habit, and switching cost. However, these studies do not use a theoretical basis to discuss the relevance of these factors, and they only explain the impact of these factors on users' IT/IS switching based on superficial reasons. To fill this gap, by applying the PPM model of migration theory, this study proposes an exterior-interior factor model to explain why users want to switch from their current health apps to other apps. In order to clearly analyze the factors affecting switching intention for health apps, this study divides the factors into positive and negative drivers.

Second, previous research identifies four types of decisions about using health apps, including abandoning use, limiting use, switching apps, and continuing use (Vaghefi and Tulu, 2019). However, previous research has not addressed the conditions or antecedents of the decision on health apps switching. Contrarily, in this study, we propose a research model that attempts to explain why users have switching intentions of current health apps. Our results reflect that in addition to known functional conditions, users are also affected by *social influences*, *(dis)satisfaction* and *habits*, which lead to switching intentions of health applications. We believe these results fill another gap in previous research.

Third, this study provides new empirical evidence that social influence has an impact on users' switching intention. However, sources of social influence with respect to individuals are from online acquaintances or reviews that ought to be investigated further. If the decision to switch apps is influenced by online friends, then the relationship types and roles of online friends should be further explored. However, if it is online reviews that lead to users' switching behavior, then it is necessary to further understand the process of generating online reviews. This is because, at present, scholars do not have a consistent understanding of the construction of social influence. Although we know the importance of social influence, we still need to clarify the connotation of social influence in order to build a more robust model.

Fourth, most of the technology analyzed in past studies are personal IT products and services, such as web browsers (Bhattacherjee et al., 2012), smartphones (Fan and Suh, 2014), online games (Hou et al., 2011), and instant messengers (Sun et al., 2017). Although these technology products can represent the status of personal use of technology, the results of these studies cannot fully explain the reasons for switching health apps (Vaghefi and Tulu, 2019; Xiong and Zuo, 2023); particularly, health apps record sensitive information of users. Meanwhile, we prove that whether a person continues to use a health app is related to whether others continue to use the app. Thus, addressing the usage differences between health apps and other personal IT, and to identify the factors that affect switching intentions of health apps is another contributions of this research.

6.2 Practical Implications

Switching of a health app means that the user loses interest in the app, which also means that the development cost invested by the app company is wasted. Therefore, reducing the user’s switching intention is a way for companies to keep profits. For these purposes, this study provides several practical recommendations for app designers, companies, and executives.

First, to increase the extent of social influence, app providers should figure out some ways to enhance users’ loyalty for avoiding switching intention. For instance, they may adopt some viral approaches, such as Podcast or Clubhouse, to talk about the healthcare and medical topics and promote their own apps simultaneously. As a result, the users are more likely to be held in the online community and less likely to consider switching to other health apps.

Second, satisfaction affects the willingness to switch health apps. Therefore, application companies should think about how to reduce customer dissatisfaction so that users do not switch away from their existing health apps. Application companies must also understand why customers are dissatisfied with existing applications and improve the product quality so that customers do not develop the willingness to switch to other health app providers.

Third, user preferences and habit affect user switching. Our results show that the greater the user's habit of using the product, the lower the user's switching intention. Providers should think about how to make users get accustomed to the service of the operator. For instance, different marketing strategies can be formulated for different focus individuals to make users more dependent on products, strengthen corporate image or word of mouth, and implement corporate social responsibility.

6.3 Limitations and Future Research

This study inevitably faces some potential limitations that can be further investigated in the feature. First, the purpose of this study is to find the factors that influence users' switching intentions of health apps; therefore, this research may not be applied to other types of apps (e.g., gaming apps, social networking apps, and tool apps). Researchers can consider modifying this research model to explore other types of apps in the future. Second, this study is a cross-sectional study in which the time period of data collection is limited to one month. Besides, the number of the questionnaire samples is only 218, meaning that the sample may lack representativeness. If we had more time to collect a greater number of samples, the results would be more stable and credible. Third, there are actually many factors that may affect the willingness to switch health apps. Nonetheless, based on the concept of push-pull drivers, this study considers only five factors: *attractive alternatives*, *social influence*, *dissatisfaction*, *switching costs*, and *habits*; we might ignore other important factors that deserve further investigation. Fourth, because the participants in this study are all Taiwanese, the research results may be dissimilar to the situations in other countries due to culture difference. Further researchers can consider verifying this model in different cultural contexts. Finally, this study focuses on health apps on mobile devices (cell phones or tablets), and does not cover other devices/hardware with similar functions, such as IoT "Sport" devices, health bracelets or smart watches. We suggest that related research on smart wearable devices can be developed in the future.

6.4 Conclusion

The purpose of this study is to investigate users' switching intentions of health apps. We develop the research model and conduct a survey to examine factors and draw conclusions. First, *social influence*, *dissatisfaction* with the current health app, and *habits* have significant impacts on *switching intention*. Second, the impact of *attractive alternatives* on *switching intention* is relatively small. Third, the impact of *procedural switching costs* on *switching intentions* is insignificant. Finally, *procedural switching costs* do not affect *switching intentions* of users who are dissatisfied with their current health app.

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Appendix. Questionnaire items

Part I Questionnaire items

Attractive alternatives (Jones et al., 2000; Hou and Shiau, 2020)

AA1: If I needed to change the current Health App, there are other good Health Apps to choose from.

AA2: I would probably be happy with the operations and functions of another Health App.

AA3: Compared to the current Health App, there are other Health Apps with which I would probably be equally or more satisfied.

AA4: Compared to the current Health App, there are not very many other Health Apps with which I could be satisfied.

Social influence (Mathieson, 1991; Wong et al., 2019; Chong et al., 2022)

SI1: People who are important to me would want me to switch the current Health App.

SI2: People who influence my behavior would think I should switch the current Health App.

SI3: People whose opinions I value would prefer me to switch the current Health App.

Dissatisfaction with the current health app (Liao et al., 2011; Bhattacherjee et al., 2012; Fan and Suh, 2014; Hou and Shiau, 2020)

DIS1: I feel dissatisfied about my overall experience of the current Health App use.

DIS2: I feel displeased about my overall experience of the current Health App use.

DIS3: I feel frustrated about my overall experience of the current Health App use.

DIS4: I feel terrible about my overall experience of the current Health App use.

DIS5: I feel dissatisfied about the demand of the current Health App use.

Procedural switching costs (Fan and Suh, 2014)

PSC1: It would take a lot of mental effort to familiarize myself with a Health App’s operations and functions after switching.

PSC2: I would have to expend a lot of mental effort to learn about the operations and functions offered by a Health App.

PSC3: It would take a lot of time to familiarize myself with a Health App’s operations and functions after switching.

PSC4: I would have to expend a lot of time to learn about the operations and functions offered by a Health App.

Habits (Limayem et al., 2007; Limayem and Cheung, 2011; Bhattacherjee et al., 2012; Chong et al., 2022)
HAB1: Using the current Health App has become automatic to me.
HAB2: Using the current Health App is natural to me.
HAB3: When faced with a health need, using the current Health App is an obvious choice for me.

Intention to switch other health apps (Bhattacherjee et al., 2012; Chong et al., 2022)
IS1: I would likely switch to other Health Apps the next two weeks.
IS2: I plan to abandon using my current Health App within the next two weeks.
IS3: I intend to switch from my current Health App to others within the next two weeks.

Part II Basic information
See Table 2

Author Biography

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Cheng-Kui Huang is a Professor in the Department of Business Administration, National Chung Cheng University of Taiwan. His current research interests include data mining/business intelligence/big data, information management, e-commerce, and soft computing. He has published papers in *Decision Support Systems*, *IEEE Transactions on Systems*, *Man and Cybernetics − Part B*, *European Journal of Operational Research*, *Information Systems Frontiers*, *Information Technology and Management*, *International Journal of Information Management*, *Data & Knowledge Engineering*, *Information Sciences*, *Fuzzy Sets and Systems*, *Journal of Systems and Software*, *Computers & Education*, *Knowledge-Based Systems*, *Applied Soft Computing*, *Telematics and Informatics*, *Applied Intelligence*, *Intelligent Data Analysis*, etc.

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