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An Investigation into the Adoption Behavior of mHealth Users: From the Perspective of the Push-Pull-Mooring Framework

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Abstract: As an important branch of the modern electronic health care services, mobile health applications (mHealth APP) have been widely accepted as a novel health care-providing platform. Based on mobile communications, mHealth is operated on smart terminals such as smart phones, tablet computers, wireless devices or wearable devices, providing multi-channel, multi-terminal and multi-network services. Because mHealth is not restricted by time and space, it serves as a more effective disease management tool for communications between patients and medical workers. In the background of "Internet+", this study aims to explore the internal adoption behavior of mHealth users to improve the efficiency of medical services, reduce medical costs, and enrich the "Internet + medical health" research. Guided by the push-pull-mooring framework (PPM), this study proposes a conceptual model of mHealth users' adoption behavior. A specially designed survey was used to collect data on users' adoption behavior (n = 183). SPSS 25.0 (Guiyang, China) and AMOS 21.0 are used for data analysis. The results show that users' adoption attitude partially mediates the relationship between the adoption intentions and three key factors (inconvenience, APP attractiveness, and high risk). The adoption intention also partially mediates the relationship between adoption attitude and adoption behavior. Peer influence does not have a direct effect on adoption intention, but it shows a statistically significant indirect effect on adoption intention and adoption behavior through adoption attitude. The negative effect of high switching cost is not significant for both adoption attitude and adoption intention. This study elucidates the internal mechanisms underlying mHealth users' adoption behavior. The findings can help mHealth providers to arouse more users' adoption behavior, improve the quality of medical services, and reduce medical costs.

Keywords: mHealth; PPM model; adoption intention; adoption behavior

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1. Introduction

With the increasing popularity of 4G and 5G networks, the continual updates of operating systems such as iOS, and the declining prices of smart terminals such as smartphones, and tablet computers, mobile internet technologies have witnessed unprecedented development, ushering in a new digital era [1,2]. Among these technologies, mHealth is the provision of medical services through the use of mobile communication technologies such as mobile phones, PDAs, and satellite communications [3]. In the background of "Internet + health care", users' demand for services related to health, wellness, health care, and chronic disease management has greatly increased. The traditional offline medical service model can no longer meet users' needs for convenient, effective, and individualized health management services. Several studies had proven the positive effects of mHealth technologies on the development of medicine, user physical health, and health behaviors [4,5]. For example, patients with chronic diseases and elderly patients can use mobile medical devices to monitor their real-time body data for medical intervention and efficient health management. Medical information platforms can provide users with medical information or services such as medical health consultation, online appointment, online consultation, and report inquiry through medical APPs. From this perspective, mHealth APPs have transformed the traditional model of medical services. Because of its unique features such as ease of use, practical utility, and convenience, mHealth APPs have played a very important role in the delivery of medical services, opening a new direction for users' health management [6–8].

The concept of "mHealth" was first proposed by Istepanian and colleagues as a medical system that uses mobile communication and network equipment to provide health care services [9]. In this study, mHealth is operationalized to represent light health care with mobile terminal equipment as the carrier, which mainly include online medical services such as appointment, consultation, and medicine e-commerce, etc. Data have shown that the COVID-19 pandemic turned out to be a golden opportunity for the online industry, with demands for mHealth services witnessing rapid growth and market revenues reaching 54.47 billion yuan in 2020. Due to the convenience and service coverage of mHealth apps, better disease prevention and control effects have been achieved [10,11]. Alaiad et al. found that mHealth provides users with more convenient access to medical information inquiry and health services, especially in the areas of online appointment and consultation [12]. Over 50% of the respondents in this study reported that convenience of registration was the unique advantage of mobile medical services, which greatly improved users' medical experience and convenience. Similarly, Tu et al. found that users could search the price of medical services online and find cheaper treatment options [13]. Furthermore, since mHealth is not limited by time and place, patients are freer in making personal choices or decisions. Moreover, an additional benefit was that patients reported becoming more actively involved in self-health management during their subconscious exposure to mHealth services. As a conclusion, mHealth is becoming a new direction for the development of the medical field due to its myriad advantages such as convenience, low medical cost, and high efficiency. The share of mHealth services in the health care market is expected to grow exponentially.

In the last few years, research on the adoption and use behavior of mHealth APPs has been conducted worldwide. For example, Hung et al. explored the adoption of mHealth management services based on the technology acceptance model (TAC) [14]. Rai et al. integrated findings from research on the TAC, technology assimilation theory, as well as consumer behavior and health informatics [15]. Based on user factors, features of medical services, and demographic characteristics, they explored a wide variety of issues, ranging from user intention to the selection of different providers. In the existing research, many scholars focus mainly on mobile medical services related to technical characteristics [16–18], application platform design [19,20] or factors related to the external environment that effect users' adoption and the use of mHealth [21,22]. Conway et al. found that 71% of patients expressed a willingness to use mHealth APPs, but only 7% actually used them [23]. The reason for the difference in acceptance behavior before and after use may be related to the characteristics of the APP itself and the use environment. In addition, based on rational behavior theory, Zhang et al. explored the influence of gender on the adoption behavior of mHealth APPs, and found that males were more willing to adopt mHealth services than females [24]. Based on TAC, Cho further revealed that perceived usefulness, perceived ease of use, and satisfaction could also significantly affect the willingness to adopt mHealth [25]. Meanwhile, Lee et al. confirmed that usefulness, convenience, and monetary value are important factors that influence users' adoption of mHealth services [26].

The push-pull-mooring model was firstly used to study migration in demography and initially only included push and pull factors to explain people's migration behavior [27]. Subsequently, Moon et al. attracted mooring factors to explain why people prefer to stay where they are rather than choose to migrate in terms of individual and social factors [28]. Since the PPM theoretical model provides a powerful explanation for user channel switching behavior, scholars have applied this theory to explain consumer channel migration behavior in recent years. Based on the PPM model, Bansal et al. elaborated and summarized consumer channel migration behaviors [29]. In their account, push refers to the positive factors that prompt consumers to leave the original channel, which is usually derived from the inadequacies of the original channel; pull refers to the positive factors that stimulate consumers to migrate to the new channel, which is mainly due to the attractiveness of the new channel; and mooring refers to the difficulties or resistance consumers face in the process of migration, which are regarded as negative factors that are usually derived from costs, risks, etc., in the migration process. Mobile health care adoption behavior is essentially a migration behavior of users from offline physical hospitals to online mobile health care services, and a migration behavior of users from traditional physical health care sites to online virtual health care sites, which is also influenced by three forces: push, pull and mooring. From the above analysis, it is clear that the PPM analysis framework model has good explanatory power for the adoption behavior of mHealth users. Many scholars have studied the influencing factors of user channel selection. For example, Albesa investigated this question through questionnaires and found that perceived convenience, social relationships, channel knowledge, and individual factors were among the major factors that influenced users' channel selection [30]. Verhoef pointed out that users make channel selection decisions based on channel attributes and channel attractiveness [31]. In addition to these factors, customer-enterprise interaction and reputation also affect consumers' channel migration behavior [32–34]. Pookulangara showed that factors such as consumers' subjective attitude also significantly affected the willingness to adopt online channels [35]. Scholars such as Hsieh et al. studied users' migration from blog to social network platforms based on the PPM model [36]. By using this model, Chang et al. also explored users' willingness to migrate from physical retail channels to mobile retail channels and arrived at similar conclusions [37]. In fact, the adoption of mHealth is a kind of information system acceptance behavior, which refers to the behavior of users migrating from traditional physical medical places to online virtual medical places. This type of migration behavior is also subject to three forces, namely, push, pull, and mooring.

In conclusion, mHealth is an emerging form of mobile technology in the medical field, where users play a central role in mHealth acceptance and adoption. However, inadequate attention has been given to users' individual factors in the existing research. Most existing studies focus on many factors such as the external characteristics, system design, technical environment, and usage context of mHealth [17,21,38], and few studies analyze the impact of users' subjective perceptions on adoption behavior. In this paper, we select the micro perspective of individual perceptions and consider the direct or indirect influence of users' psychological emotions on the intention to use in a comprehensive manner. Therefore, to explain and predict the adoption behavior of mHealth users, this study adopts the PPM model as a guiding framework and proposes a conceptual model of mHealth users' adoption behavior. With this model, this study aims to explore the adoption behaviors of mHealth users in the background of "Internet +". The following research topics will be addressed:

(1) Why do mHealth users have some certain adoption behaviors? What are the factors that influence these users' adoption behavior?
(2) What role do PPM-related variables play in affecting the mHealth users' adoption behavior?

Although the PPM model has shown some reasonable explanations to the users' adoption behavior, very few studies have applied it to study the adoption behavior of mHealth users. Therefore, this study aims to fill this gap by adopting the PPM model to conduct an empirical study on the adoption behavior of mHealth users. This research has important implications to not only enrich the theories of behavior adoption specially for the mHealth services, but also provide a reference for health care institutions to make developing strategies.

2. Research Hypotheses and Model Construction

2.1. Research Hypotheses

The common medical treatment situation in many domestic hospitals is ironically described by the phrase "queue for 3 h and see a doctor for 3 min". This inefficient situation reflects the inconvenience of the traditional health care treatments in China today. As an alternative to this conventional medical treatment mode, mHealth can effectively meet users' demands at almost anytime and anywhere. Through mobile terminal devices, users can easily and quickly obtain various medical services, which alleviates the difficulties involved in seeing a doctor under the traditional medical model. Brown showed that convenience is a defining feature of mHealth services that distinguishes it from traditional health care [39]. Lai et al. also found that the inconvenience of traditional health care positively predicted consumers' attitudes toward and willingness to migrate to mobile online channels [40]. The more convenient users perceived mHealth to be the stronger the adoption attitude and willingness to adopt mHealth. Therefore, this study speculates that mHealth services can greatly meet users' needs for convenient medical treatment, thus prompting more users to turn to mobile channels for medical consultation. Accordingly, the following hypotheses are proposed:

H1. *Inconvenience has a significantly positive effect on users' adoption attitude.*

H2. *Inconvenience has a significantly positive effect on users' adoption intention.*

Hu et al. found that word-of-mouth recommendation has become a major source of information of product quality for consumers and users [41]. In addition, Markovic et al. revealed that word-of-mouth recommendation has a huge impact on users' attitudes and behaviors, mainly because the peer recommendations can greatly reduce the difficulty of making choices and enhance their confidence in the suggested products [42]. Meanwhile, De Bruyn A showed that the huge number of unfamiliar comments on social media from different perspectives could provide some professional insights on health care products [43]. The friendliness towards the mHealth app from the user's family and friends could have a strong positive influence on the user. In other words, peer influence has a positive effect on users' adoption attitude and willingness to adopt. Based on this, this study proposes another two major hypotheses:

H3. *Peer influence has a significantly positive effect on users' adoption attitudes.*

H4. *Peer influence has a significantly positive effect on users' adoption intention.*

Due to the rapid spread of mobile terminal equipment, domestic mHealth APPs came into the public view in the early 2011. The attractiveness of mHealth APPs is also reflected in users' perceived benefit. Ueland et al. indicated in the BRA model of consumption intention and consumption behavior that consumers' perceived benefit was one of the most important factors that directly affect consumers' purchase intention [13]. Perceived usefulness is also one of the important attractions of mHealth APPs. Using the TAC framework, Hung et al. found that perceived usefulness and ease of use had a significant effect on the adoption attitude and willingness to adopt mHealth management services [14]. As a result, this study hypothesizes that, compared with traditional health care services, the unique attractiveness of mHealth APPs can improve users' attitudes and willingness to use mHealth services, thus encouraging the migration from traditional medical channels to mHealth APPs. The following two hypotheses are proposed:

H5. *The attractiveness of mHealth APPs has a significantly positive effect on users' adoption attitudes.*

H6. *The attractiveness of mHealth APPs has a significantly positive effect on users' willingness to adopt*.

During migration of medical channels, users tend to pay a certain conversion cost. In the existing research, Chiu et al. pointed out that switching costs could play a very important role in the migration behavior of consumers from offline to online channels [44]. Ansari et al. further showed that lower switching cost could encourage users to migrate from offline to online channels [45]. In addition, Kauffman et al. indicated that consumers are less likely to switch purchasing channels when switching costs are high [46]. Since users have become accustomed to offline channels for health care, they may have deep concerns over the treatment effect of mHealth APPs, and even refuse to accept mHealth services. In this study, switching cost is defined as the increased cost when users transfer from offline traditional medical channels to online mHealth APPs. Such costs will negatively affect users' attitudes and willingness to adopt. Based on these analyses about the switching cost, this study proposes two following hypotheses:

H7. *High switching cost has a significantly negative effect on users' adoption attitude*.

H8. *High switching cost has a significantly negative effect on users' willingness to adopt*.

Since mHealth services are carried out in a virtual on-line environment, they involve more uncertainty and risks compared with traditional health care channels. Some western scholars have discussed the impact of risk perception and risk attitude on users' adoption [47–49]. Park et al. found that when individuals perceived risks, they would experience worry, uncertainty, restlessness, anxiety, and cognitive dissonance, and become anxious about the instability of information systems [50]. In addition, Kuhlmeter also showed that perceived risk was negatively correlated with consumer purchase intention [51]. Similarly, Cocosila et al. contended that due to the imperfect and open framework structure of mobile technology, it is likely that users may perceive threats to their privacy and physiological safety during online medical diagnosis [52]. As a result, this study proposes the following hypotheses:

H9. *High-risk tools have a significantly negative effect on users' adoption attitudes*.

H10. *High risk has a significantly negative effect on users' adoption intention*.

Adoption attitudes are the positive or negative feelings that an individual has when using a system and assessing the impact of performing a behavior, and an individual's attitude affects their willingness to act accordingly [53]. Willingness to adopt is a behavioral intention, where people's attitudes towards a substance and a behavior influence their behavioral intentions and ultimately determine the behavior, and the stronger their behavioral intentions, the more they will act on them [54]. Adoption intentions are a key predictor of adoption behavior, and the higher the user's intention to adopt, the more likely they are to adopt the new product [55,56]. Ajzen clearly pointed out that attitude variables directly affected behavioral intention in his research [57]. Based on online survey data, Postmes et al. also found that people's attitudes towards environmental activities could strongly predict their behavioral intention [58]. Therefore, we hypothesize that more positive users' attitude towards mHealth treatment could lead to higher adoption willingness and behavior while stronger users' willingness to adopt could cause higher possibility of adopting the mHealth services. Lastly, this study proposes three following hypotheses about the users' adoption attitude:

H11. *Users' adoption attitude has a significantly positive effect on users' adoption intention*.

H12. *Users' adoption attitude has a significantly positive effect on users' adoption behavior*.

H13. *Users' adoption intention has a significantly positive effect on users' adoption behavior.*

2.2. Modelling by Push-Pull-Mooring Framework

Based on the PPM framework, this study examines users' mHealth adoption behavior from the perspective of push factors, pull factors and mooring factors. Among them, the inconvenience of traditional medical treatment channels is the push factor, peer influence and the attractiveness of mHealth APPs are the pull factors, and the high switching cost and high risk are mooring factors. The specific conceptual model is shown in Figure 1:

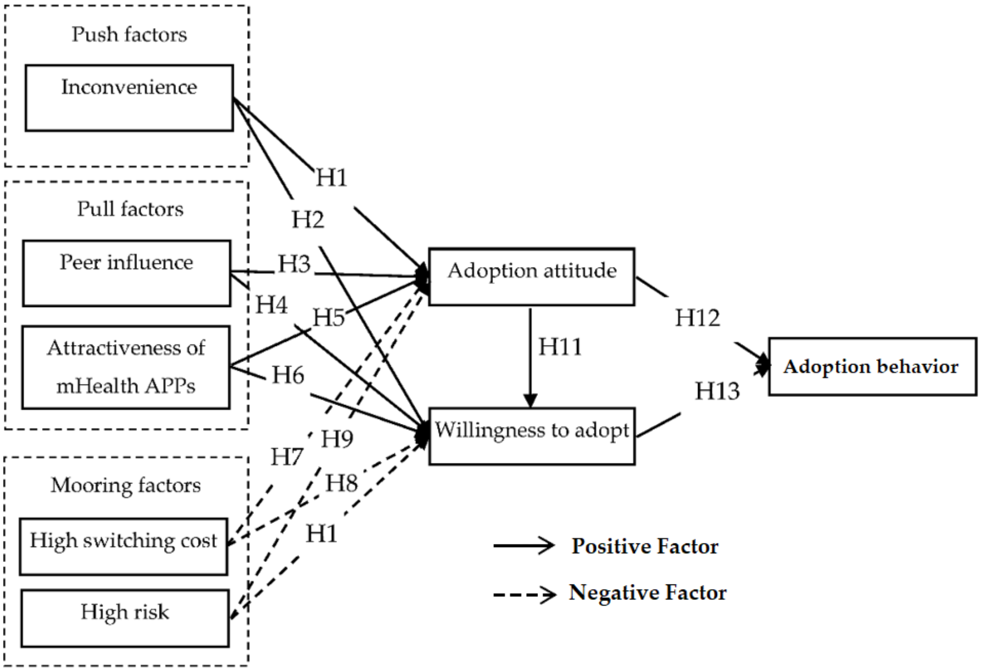

Figure 1. Theoretical model of mobile medical users' adoption behavior.

3. Data Collection and Methodology

3.1. Data Collection and Variable Measurement

First, a questionnaire entitled "Questionnaire on mHealth Users' adoption Behavior from the Perspective of the Push-Pull-Mooring Framework" was designed. To help respondents understand the meaning of the research topic, the concept of mHealth was explained in the first part of the questionnaire. Furthermore, we also listed some common medical APPs in the questionnaire to give the respondents a more intuitive understanding, such as Ping An Good Doctor, Good Doctor Online, Chunyu Handheld Doctor, etc. Furthermore, a screening question was included in the questionnaire: "Have you ever used a mHealth APP?" If a respondent answered "No", this response would be excluded as invalid. Since mHealth services are not very popular in China, using printed questionnaires would be relatively inefficient and uneconomical to identify enough respondents who qualify for the research. The data collection method used in this paper is snowball sampling. Snowball sampling is the process of selecting and interviewing a random number of respondents, asking them to provide additional respondents who belong to the overall target of the study, and selecting subsequent respondents based on the leads formed. James S. Coleman was the first to design and use snowball sampling for non-probability sampling [59], and Goodman further developed peer-driven snowball sampling for hard-to-reach populations [60]. Becker gradually developed snowball sampling as an important standard for qualitative research and textual analysis in sociological methods [61]. First, a group of respondents were randomly sampled. After interviewing these respondents, we then asked them to help recruit other respondents who met the research objectives through WeChat Moments. In the end, 247 questionnaires were recovered, with 183 of them being valid (74.1%). The mHealth APP users were relatively young, with 151 users under the age of 40 (82.5%). In terms of educational background, 137 users (74.9%) had a bachelor's degree or above.

All items were measured on a 7-point Likert scale, ranging from 1 (completely disagree) to 7 (completely agree). For the push factor, the inconvenience variable was derived from Yoon et al. [62]. Among the pull factors, the peer influence variable was derived from Brown et al. and Clasen et al. [63,64], while the attractiveness variable of mHealth APPs was derived from Ueland et al. and Hung et al. [14,65]. Among the mooring factors, the high switching cost variable was derived from Klemperer, and the high-risk variable from Wood et al. [38,66]. Adoption attitude, willingness to adoption, and adoption behavior were derived from the studies of Taylor et al. Golleitzer and Pavlou et al., respectively [67–69].

3.2. Research Methods

Based on the PPM framework, this study constructed a conceptual model of mHealth users' adoption behavior. SPSS 25.0 and AMOS 21.0 statistical software were used to validate the model based on the questionnaire data. Specifically, confirmatory factor analysis (CFA) was used to test the reliability and validity of the model.

4. Results and Analysis

4.1. Reliability and Validity

CFA was performed to examine the convergent validity and discriminant validity of each variable using AMOS 21.0. It can be seen from Table 1 that the questionnaire has adequate reliability, with the internal reliability (Cronbach's alpha) of each factor ranging from 0.658 to 0.802. The standardized factor loading of all variables exceeds 0.6 and are statistically significant at the nominal level of 0.05. The Average Variance Extracted (AVE) of the factors are all higher than 0.5, indicating good convergent validity. Meanwhile, Table 1 also shows that the composite reliability (CR) of 8 variables is above 0.7, exceeding the standard of 0.7, indicating that the scale has good composite reliability.

Discriminant validity was tested by calculating the correlation between factors as shown in Table 2. There was a significantly negative correlation between high switching cost and high risk and the other 6 variables ($r = -0.390\sim-0.116$, $p < 0.05$), and the remaining variables were significantly positively correlated ($r = 0.277\sim0.0.612$, $p < 0.05$). The square root of each factor AVE on the diagonal was between 0.739 and 0.888. All are higher than 0.5, and all larger than the correlation coefficient between variables, indicating that the scale has good discriminant validity.

Table 1. Confirmatory factor analysis of the measurement model.

Latent Variable	Items	Standardized Loading	Cronbach's Alpha	CR	AVE
Inconvenience	3	0.66 0.75 0.80	0.688	0.782	0.546
Peer influence	3	0.91 0.92 0.83	0.747	0.917	0.788
Attractiveness of mHealth APPs	3	0.75 0.83 0.68	0.694	0.799	0.571
High switching cost	4	0.89 0.87 0.76 0.81	0.798	0.901	0.696

Table 1. *Cont.*

Latent Variable	Items	Standardized Loading	Cronbach's Alpha	CR	AVE
High risk	3	0.78 0.87 0.61	0.683	0.806	0.579
Adoption attitude	3	0.76 0.81 0.64	0.658	0.783	0.548
Willingness to adopt	4	0.64 0.85 0.95 0.89	0.802	0.904	0.707
Adoption behavior	3	0.75 0.82 0.68	0.696	0.795	0.566

Table 2. The square root of the factor AVE value and the correlation coefficient matrix between the factors.

	SD	1	2	3	4	5	6	7	8
1. Inconvenience	0.89	0.739							
2. Peer influence	1.43	0.363	0.888						
3. Attractiveness of mHealth APPs	0.84	0.365	0.478	0.756					
4. High switching cost	1.20	−0.187	−0.342	−0.296	0.834				
5. High risk	0.76	−0.116	−0.199	−0.269	0.196	0.761			
6. Adoption attitude	0.82	0.358	0.465	0.471	−0.320	−0.323	0.740		
7. Willingness to adopt	0.77	0.466	0.539	0.612	−0.372	−0.390	0.574	0.841	
8. Adoption behavior	0.63	0.277	0.385	0.382	−0.296	−0.309	0.416	0.481	0.752

CFA was used to test the measurement model with the results shown in Table 3. The model fit indices are: x^2/df = 1.410, GFI = 0.859, CFI = 0.958, IFI = 0.958, AGFI = 0.820, RMSEA = 0.047. Although GFI is slightly less than the cutoff of 0.90, all the other indices are in the acceptable range, suggesting that that the model fit the data well.

Table 3. Recommended value and actual value of model fit index.

Fit Index	x^2/df	GFI	AGFI	CFI	IFI	RMSEA
Recommended value	<2	>0.90	>0.80	>0.90	>0.90	<0.08
Actual value	1.410	0.859	0.820	0.958	0.958	0.047

Note: x^2/df is the ratio of chi-square value to degrees of freedom, GFI is the goodness-of-fit index, AGFI is the adjusted goodness-of-fit index, CFI is the comparative fit index, NFI is the normative fit index, and IFI is incremental fit index, and RMSEA is the root mean square of approximation.

In this research, Harman's single-factor test is used to test for common method bias problems. Hermann's one-way test is a non-rotating exploratory factor analysis of the questionnaire measurement scale, observing how many factors with eigenvalues greater than 1 are precipitated, and how much total variance these factors explain, where the variance explanatory amount of the first factor exceeds half (50%) of the total variance explanatory amount; if the explanatory amount of variance of the first factor does not exceed half of the total absovation explanatory amount, it indicates that there is no single factor in the data that can explain most of the variance, and the common method is not seriously biased [70]. The results of Hermann's one-way test analysis are shown in Table 4, and a total of 8 factors with eigenvalues greater than 1 are precipitated, which explain a total of 75.744% of the total variance, of which the variance of the first factor is only 12.443%, which is not more than one-fifth of the total variance explanation. Therefore, there is no common method bias in this study.

Table 4. Total variance explanation.

Composition	Initial Eigenvalues			Extract the Sum of Load Squares			Sum of Squares of Rotating Loads		
	Total	Variance Percentage	Cumulative%	Total	Variance Percentage	Cumulative%	Total	Variance Percentage	Cumulative%
1	8.935	34.365	34.365	8.935	34.365	34.365	3.235	12.443	12.443
2	2.389	9.190	43.555	2.389	9.190	43.555	2.698	10.376	22.818
3	2.054	7.899	51.454	2.054	7.899	51.454	2.561	9.849	32.668
4	1.490	5.729	57.183	1.490	5.729	57.183	2.373	9.126	41.793
5	1.396	5.370	62.554	1.396	5.370	62.554	2.300	8.848	50.641
6	1.250	4.810	67.363	1.250	4.810	67.363	2.256	8.677	59.318
7	1.148	4.414	71.777	1.148	4.414	71.777	2.216	8.521	67.839
8	1.031	3.967	75.744	1.031	3.967	75.744	2.055	7.904	75.744
9	0.668	2.569	78.312						
10	0.625	2.402	80.715						
11	0.595	2.290	83.004						
12	0.512	1.969	84.973						
13	0.500	1.922	86.896						
14	0.435	1.674	88.569						
15	0.399	1.536	90.105						
16	0.390	1.498	91.603						
17	0.333	1.281	92.884						
18	0.303	1.167	94.051						
19	0.296	1.138	95.189						
20	0.274	1.053	96.242						
21	0.234	0.900	97.142						
22	0.200	0.771	97.913						
23	0.175	0.674	98.588						
24	0.146	0.563	99.151						
25	0.116	0.446	99.596						
26	0.105	0.404	100.000						

Extraction method: Principal component analysis.

As shown in Table S1, the questionnaire begins with an explanation of the meaning of mHealth to give respondents a clear and accurate understanding of the research topic. In addition, to help respondents understand mHealth APPs more intuitively, some common medical APPs are cited in the questionnaire, such as Ping An Good Doctor, Good Doctor Online and Chunyu Palm Doctor. These measures are helpful for respondents to better understand the meaning of each question. A total of 247 questionnaires were collected in this survey, among which 183 of them were usable questionnaires. The effective rate of the questionnaires was about 74.1%. The 64 invalid questionnaires included seven duplicate cases, accounting for 2.8% of the total sample; 26 samples with consistent options, accounting for 10.5% of the total sample; 17 samples with mean values greater or less than 2 SD, accounting for 6.9% of the total sample; and 14 paper questionnaires with incomplete responses, accounting for only 5.7% of the total sample. The survey results showed that the majority of the respondents were able to complete the responses with adequate quality. As a result, the issue of non-response bias in this study is not significant.

4.2. Hypothesis Testing

As shown in Figure 2, a structural equation model (SEM) was established and empirically tested. This model hypothesized that inconvenience, peer influence, attractiveness of mHealth APPs, high switching cost and high risk are independent variables, adoption attitude and willingness to adopt are mediator variables, and adoption behavior is the outcome variable.

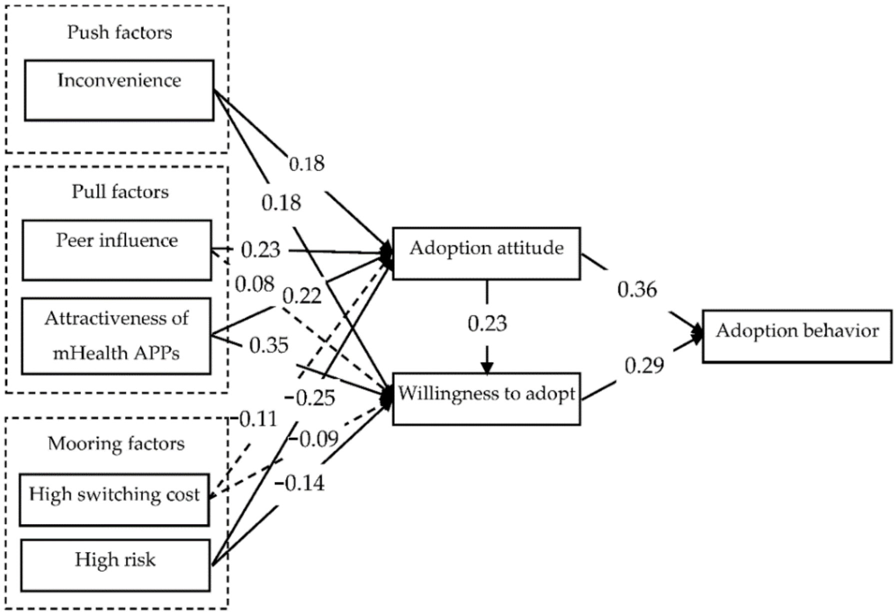

Figure 2. Structural equation test results (standardized path coefficient model). Note: The dotted line indicates non-significant paths.

The SEM model test results showed (see Table 5) that 3 hypotheses were rejected, and the remaining 10 hypotheses were supported. Inconvenience, attractiveness of mHealth APPs, and high risk showed significant effects on adoption attitude and willingness to adopt, respectively. The standardized path coefficients are 0.18 and 0.18, 0.22 and 0.35, −0.25 and −0.14, respectively, all significant at the level of 0.05. Hypothesis 1, Hypothesis 2, Hypothesis 5, Hypothesis 6, Hypothesis 9 and Hypothesis 10 were all supported. This indicates that the more inconvenient the traditional medical channels, the stronger the attractiveness of mHealth APPs and the lower the perceived risk. Additionally, this will lead to a more significant impact on users' adoption attitude and willingness to adopt, which then result in increased adoption behavior. Hypothesis 3 was supported, with peer influence having a significant impact on adoption attitude ($\beta = 0.23$, $t = 2.438$). This indicates that users' attitude towards mHealth adoption is greatly influenced by peer factors. In addition, peer influence had a positive effect on adoption intention ($\beta = 0.08$, $t = 1.091$), but this effect was not significant. Therefore, Hypothesis 4 was not supported. This may be related to users' concerns about their property, life, health as well as the safety of mHealth services as a special product. The higher the peer influence, the higher users' willingness to adopt mHealth services. Finally, a high switching cost had a negative effect on adoption attitude and adoption intention ($\beta = -0.11$, $t = -1.369$; $\beta = -0.09$, $t = -1.431$), respectively, but both effects were not significant. Hypotheses 7 and 8 were not supported, indicating that switching costs do not significantly affect the migration of users from traditional medical channels to mobile medical channels. Users' adoption attitude significantly affected adoption behavior through adoption intention (indirect effect = 0.067), and Hypotheses 11 and 13 were supported. The direct effect of users' adoption attitude on adoption behavior ($\beta = 0.36$, $t = 3.029$) was supported, indicating that the friendlier a user's attitude is towards mHealth, the higher the possibility of actual adoption. Hypothesis 12 was supported.

Table 5. Structural equation model test results.

Hypotheses	Standardized Path Coefficients	Standard Error	T-Value	Conclusion
H1: Inconvenience → Adoption attitude	0.18 *	0.090	1.999	Support
H2: Inconvenience → Willingness to adopt	0.18 *	0.079	2.405	Support
H3: Peer influence → Adoption attitude	0.23 *	0.053	2.438	Support
H4: Peer influence → Willingness to adopt	0.08	0.046	1.091	Fail
H5: Attractiveness of mHealth APPs → Adoption attitude	0.22 *	0.116	2.008	Support
H6: Attractiveness of mHealth APPs → Willingness to adopt	0.35 ***	0.105	3.803	Support
H7: High switching cost → Adoption attitude	−0.11	0.058	−1.369	Fail
H8: High switching cost → Willingness to adopt	−0.09	0.049	−1.431	Fail
H9: High risk → Adoption attitude	−0.25 **	0.117	−2.988	Support
H10: High risk → Willingness to adopt	−0.14 *	0.102	−2.107	Support
H11: Adoption attitude → Willingness to adopt	0.23 *	0.098	2.502	Support
H12: Adoption attitude → Adoption behavior	0.36 ***	0.088	3.029	Support
H13: Willingness to adopt → Adoption behavior	0.29 **	0.074	2.742	Support

Note: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$.

To sum up, the inconvenience of traditional medical treatment channels ($p < 0.05$) and the attractiveness of mHealth APPs ($p < 0.001$) showed a significant effect on adoption behavior through the mediation of adoption attitude and willingness to adopt. High risk had a significantly negative effect on adoption attitude and willingness to adopt ($p < 0.01$), while peer influence had no significantly direct effect on willingness to adopt ($p > 0.05$). However, it indirectly and significantly affected adoption through the mediating effect of adoption attitude. Intention and adoption behavior ($p < 0.05$) and high switching cost had no significantly negative effect on adoption attitude and adoption intention ($p > 0.05$).

4.3. Test of Mediation Effect

According to Baron and Kenny, a statistically significant relationship between the independent variable and the dependent variable must be established before mediation analysis can be conducted. There are two separate situations if the relationship is significant: (1) when the direct effect and the indirect effect are both significant, the mediator variable plays a partial mediating role; (2) if the indirect effect is significant but the direct effect is null, the mediator variable is said to fully mediate the relationship between the independent variable and the dependent variable [71]. Judd et al. conducted a mediating effects analysis in a social science program evaluation [72]. The mediating effect of adoption attitude and adoption intention was tested, with the test results shown in Table 6. Table 6 shows that adoption attitude played a partial mediating role in the relationship between inconvenience and adoption intention, between the attractiveness of mHealth APPs and adoption intention, and between high-risk and adoption intention. Adoption intention also played a partial mediating role between adoption attitude and adoption behavior. Besides, adoption attitude fully mediated the relationship between peer influence and adoption intention, but adoption attitude did not mediate the relationship between high switching cost and adoption intention.

Table 6. Results of the mediation effect test.

IV	M	DV	IV → DV	IV + M → DV			Mediation
				IV → M	IV → DV	M → DV	
Inconvenience	Adoption attitude	Willingness to adopt	0.466 **	0.184 *	0.179 *	0.229 *	Partial
Peer influence	Adoption attitude	Willingness to adopt	0.539 **	0.232 *	0.083	0.229*	Full
Attractiveness of mHealth APPs	Adoption attitude	Willingness to adopt	0.6121 **	0.216 *	0.345 ***	0.229 *	Partial
High switching cost	Adoption attitude	Willingness to adopt	−0.372 **	−0.108	−0.089	0.229 *	Not obvious
High risk	Adoption attitude	Willingness to adopt	−0.390 **	−0.253 **	−0.145 *	0.229 *	Partial
Adoption attitude	Willingness to adopt	Adoption behavior	0.416 **	0.229 *	0.356 ***	0.294 **	Partial

Note: IV: independent variable, M: mediator, DV: dependent variable. ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$.

5. Discussion, Conclusions, Future Direction, and Limitations

5.1. Discussion and Conclusions

In the background of mobile Internet, this study applied the PPM model to investigate the adoption behavior of mHealth users. Specifically, the influence of push, pull and mooring factors on users' mHealth adoption behavior was examined by CFA and SEM approaches based on questionnaire data analysis. The main research findings are shown below:

(1) The inconvenience of traditional medical channels and peer influence significantly affected adoption behavior through the mediating effect of adoption attitude and willingness to adopt, which are important reasons for users to seek medical treatment through the online mobile approaches. Traditional medical institutions usually have long queues, and it is difficult to book an appointment (generally, it is very difficult to book an appointment with an expert since there is only a small percentage of experienced doctors in the health care institutions). Patients usually do not obtain enough information or detailed explanations from the expert, even if the appointment has been made successfully, because the total treatment period is limited due to the large number of patients waiting behind. Most of the checkup results cannot be released on the same diagnosis day. Due to these drawbacks, patients usually spend a lot of time and money without obtaining satisfactory health care services. These inconveniences have gradually changed patients' attitudes towards the traditional offline health care services and caused them to migrate to new online mobile medical channels. Lai et al. also found that the inconvenience of traditional physical medical services has a significantly positive effect on users' attitudes and willingness to migrate to mobile Internet channels [40]. Higher recognition of the convenience of mHealth services leads to stronger adoption attitude and willingness to adopt mHealth.

(2) The attractiveness of mHealth APPs had a significantly positive effect on users' adoption attitude and willingness to adopt. The willingness of switching from traditional medical channels to mobile medical channels is proportional to the attractiveness of the mHealth services. The attractiveness of mHealth APPs mainly lies in the provision of such features as consultation with doctors, peer communication, online diagnosis and treatment, online drug purchase and health tracking management, etc. These features are attractive primarily because the patients can see a doctor without spending too much time waiting in the queues and can obtain more detailed suggestions and diagnostic feedback. Based on the TAC framework, Hung et al. showed that perceived usefulness and perceived ease of use could have a significant effect on the adoption attitude and willingness to adopt mHealth services [14]. Our study further proved that the attractiveness of mHealth APPs was a key factor affecting users' adoption behavior.

(3) Users' perceived risk had a significantly negative effect on adoption attitude and willingness to adopt mHealth services. The higher the user's risk perception of mHealth services, the weaker the adoption attitude and willingness to adopt. Users' risk perception of mHealth services mainly come from financial risks, psychological risks, and privacy security, etc. Different users could attach different weight to different risk dimensions. Jarvenpaa et al. showed that when users' trust in online merchants increases, the perceived risk will be significantly reduced [73]. Compared with the "face-to-face" medical treatment model between doctors and patients, users of mHealth services face greater privacy and financial risks. For example, they might worry about losing their private information or having their payment stolen by scammers. Users with these risk concerns would show a less positive attitude toward mHealth services and be less willing to adopt these services. Their actual adoption behavior will be affected as well.

(4) There was no significant relationship between switching cost and adoption attitude or willingness to adopt mHealth services. First, with the upgrading of mHealth APPs, the increasing investment of medical institutions in training users to seek online health care, and more official supervisions of the mHealth APPs, users' learning costs and psychological pressure are supposed to plateau instead of further increasing. Second, the personalized promotion strategies from health care institutions could also reduce patients' financial costs.

5.2. Research Direction and Future Works

In China's epidemic environment, mobile medical services help solve many of the access problems of users in an epidemic-controlled state. Through mobile terminal devices, users can easily and quickly access various medical services, which reduces the movement of people to a certain extent and meets the urgent need for epidemic prevention and control. This study conducts an in-depth investigation of mobile medical users' willingness to use mobile medical services in China, which helps domestic and foreign mobile medical service providers and developers to better optimize the design of mobile medical services to enhance users' adoption behavior. The research directions and future studies of the mHealth APPs are listed below:

(1) Develop multiple channels for medical treatments and improve the mHealth services. With the rapid development and widespread application of the mobile Internet, emerging technologies such as big data, 5G dual-gigabit networks, and artificial intelligence have provided many new opportunities for the mHealth industry. Under the catalysis of the epidemic, an increasing number of users have also begun, voluntarily or semi-voluntarily, to appreciate the convenience of mHealth services, which has greatly increased the overall scale and penetration rate of mHealth users, leading to increased popularity of mHealth services. The results of this study also found that the inconvenience of traditional medical channels had a significantly positive effect on users' attitudes and willingness to adopt mHealth services, which in turn had a significantly positive effect on users' online behavior. This further shows the advantages of mHealth services relative to conventional medical services, which not only optimizes the treatment process, but also improves treatment efficiency. We expect that it will become a trend for medical institutions to develop various channels for medical treatment. Taking the current COVID-19 pandemic as an example, although offline medical and health institutions at all levels opened online APP medical services, the number of active users was not high due to the poor user experience. In addition, different medical institutions had different APPs, with no guarantee of the quality of services and the diversified medical services were difficult to operate. This led to many users uninstalling the apps after only a brief exposure. Considering these experiences, when hospitals develop APPs, they should think about cooperating with third parties to optimize basic application functions and medical services, increase

the usefulness of the platform, and enhance user experience. Only by doing so can they attract users to adopt online mHealth services.

(2) Increase the influence of mHealth services by word-of-mouth spread and improve users' understanding of mHealth services. The results of this study showed that peer influence had a significantly positive effect on willingness to adopt mHealth and adoption behavior through the mediating effect of adoption attitude. The more positively users are influenced by their relatives and friends, the more willing they are to switch from traditional medical channels to mobile medical channels, and the greater mHealth adoption behavior. Because the mHealth industry has some requirements on private information, users may not be willing to share their health information with others. The situation is different, however, when relatives and friends are involved. Since they trust their relatives and friends, they are more willing to exchange information or share their experience. Therefore, mHealth service providers should increase the publicity of mHealth services by prioritizing word-of-mouth communication as a publicity pitch, which can raise users' awareness of such services as well as enhance their trust. In this way, more potential users will be attracted to seek medical treatment through mobile medical channels.

(3) Improve the attractiveness and users' loyalty to the mHealth APPs. The research findings showed that the attractiveness of the mHealth APP had a significantly positive effect on users' adoption behavior through the mediation of adoption attitude and adoption intention. The functions of the existing mHealth APPs can be roughly divided into several categories, such as body index monitoring, health knowledge education (e.g., diet management and exercise management), appointment booking, doctor consultation, online consultation, online drug purchase and drug management, etc. There is too much homogeneity in these services. In the future, specialized services should be provided to increase the attractiveness of mHealth APPs. Furthermore, the attractiveness of mHealth APPs to users also depends largely on the design of APP functions. Therefore, APP developers should optimize product design, refine basic functions and improve user medical service experience. For example, efforts should be made to add an element of fun to the function design; intelligent algorithms can be used to tailor notifications of health knowledge to users' preferences, and well-known experts can be invited from time to time to offer free medical services. The goal is to make these APPs not only a convenient medical channel, but also an efficient social interaction platform for users, so users feel motivated to continue using these APPs.

(4) Standardize the mHealth health care services. The mHealth industry involves property, life, health, and safety, but all of these factors are carried out in an online environment. Therefore, it is understandable that most users would be worried about potential risks when using mHealth APPs. Among the top of their concerns are privacy protection, prices, and usefulness. As the domestic mHealth market is still in its infancy, it also faces many problems such as legal loopholes and lax market oversight. Therefore, it is necessary to intensify efforts to support the development of mHealth services. There should be continued innovation to improve on previous mHealth services. On the other hand, oversight of mHealth services should also be put on the table, such as formulating relevant laws and regulations and setting up relevant industry standards. Risk assessment and operation supervision should be frequently implemented for mHealth APPs, with particular attention to the safety of a user's life, property and privacy. Through these efforts, mHealth APPs can gradually win over people's trust and become a reliable platform for seeking medical services.

5.3. Social Impact

At present, countries around the world are facing different degrees of health care problems such as the imbalance of medical resources and medical reform. Mobile healthcare has changed the traditional healthcare model of the past, which will help to significantly improve the efficiency of healthcare resource allocation, reduce social healthcare costs and improve people's overall health. In addition, mHealth services can improve the treatment and coverage of healthcare, increase access to healthcare information, services and skills, as well as promote positive changes in health behaviors, for example, in the prevention of emergency and chronic diseases. This study combines the characteristics of mHealth and the individual cognitive factors of users to explore the factors influencing mHealth users' intention to use it, which will help mHealth service providers to provide accurate and effective mHealth services to their users, continuously improve their access experience and enhance their intention to continue to use it. More importantly, the results of the study will help promote the widespread acceptance and use of mHealth by users worldwide and promote the sustainable development of mHealth services.

5.4. Limitations

The limitations of this study are listed as the follows: (1) the respondents in this study are mostly in the ages between 18 and 40. The findings are not valid for people out of these age groups. Future research can increase the diversity of the respondents and expand their age groups. (2) The survey methods need to be further refined and expanded. Follow-up research may use a combination of scenario experiments and questionnaire surveys to triangulate users' adoption behavior regarding mHealth services. (3) This study does not examine whether demographic variables such as gender and age could moderate the simulation results. Future studies could explore whether they are important moderators in the analysis model.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su142114372/s1, Table S1: Questionnaire on mHealth Users' adoption Behavior from the Perspective of the Push-Pull-Mooring Framework.

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