Understanding gender differences in mHealth apps continuance: a modified protection motivation theory

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Received 12 September 2022
Revised 6 October 2022
Accepted 6 October 2022

Abstract

Purpose – This paper aims that mobile health (mHealth) applications have emerged as a key tool to support public health. However, there are only a few studies examining the influences of health-related ascribes on continuance intention to use mHealth apps and how these influences are contingent on gender in the mHealth app using context.

Design/methodology/approach – This study takes the protection motivation theory as a theoretical framework to examine the ordered relationship between threat and coping appraisals and their impacts on continuance intention to use mHealth apps. In addition, this study further extends the literature on gender differences into the mHealth app's context to investigate the moderating role of gender. The suggested hypotheses are confirmed by a structural equation modeling approach and multigroup investigation employing survey data of 345 users of Spring Rain Doctor in China, a typical mHealth app.

Findings – The findings suggest that the impact of perceived disease threat on user's continuance intention is mediated entirely by coping appraisals. Furthermore, the three coping appraisals' impacts are contingent upon gender. Specifically, response efficacy is more crucial for male users in forecasting continuance intention, whereas self-efficacy and response cost have a more salient influence on continuance intention for female users.

Originality/value – This study examines the ordered influences of threat and coping appraisal, moderated by gender, on continuance intention on use mHealth apps. These findings could contribute to relevant theoretical and practical implications.

Keywords Mobile health, Continuance intention, Protection motivation theory, Gender

Paper type Research paper

1. Introduction

With the popularity of mobile technology and increasing need for access to health-related information, mobile health, known as mHealth, has emerged. The application of mHealth has been employed extensively to provide new services, which have not only transformed health delivery systems but also enhanced the effectiveness of healthcare services (e.g. Birkmeyer, Wirtz, & Langer 2021). As of 2017, there were 325,000 mHealth apps available on all major app stores (Reseach2guidance, 2017). In 2020, the number of mHealth users increased to 635

Funding: This work was supported by the National Natural Science Foundation of China (Award Number: 71402159).

Declaration of interest: No potential conflict of interest was reported by the author(s).

Journal of Electronic Business & Digital Economics
Vol. 1 No. 1/2, 2022
pp. 225-247
Emerald Publishing Limited
e-ISSN: 2754-4222
p-ISSN: 2754-4214
DOI 10.1108/JEBDE-09-2022-0032

million, and the market size of mHealth reached about US $8.04 billion (iiMedia, 2021). Furthermore, despite the significant advantage of health apps in assisting people to effectively manage their health, people's use of these technologies frequently lasts only a short period (Kim, Kim, Lee, & Kim, 2019; Krebs & Duncan, 2015). This proposes a need to delve more deeply into mHealth app users' continuance intention (Luo, Wang, Li, & Ye, 2021).

Previous studies have extensively examined factors influencing users' continuance intention of e-health/mHealth service employing existing technology acceptance theories, including theory of planned behavior (TPB), theory of reasoned action (TRA), technology acceptance model (TAM) and expectation-confirmation theory (ECT), and explicated the function of different constructs (e.g. perceived benefit, perceived ease of use, attitude, perceived value, trust, confirmation, service quality and satisfaction) in the intention to continue use mHealth apps (Akter, Ray, & D'Ambra, 2013a; Hossain & Alamgir, 2016; Leung & Chen, 2019). However, these theoretical models have constraints in explaining the mHealth apps' continuance mechanism because they have paid little attention to the health attributes of mHealth services (Birkmeyer *et al.*, 2021). Preventing health hazards and sustaining security may motivate users' behavior toward mHealth (Milne, Sheeran, & Orbell, 2000). It is proposed that there should be health-specific factors that gain significance in the context of mHealth services (Liu & Tao, 2022).

The protection motivation theory (PMT) mainly focuses on the relationship between security motivation and human behavior and is extensively employed in the field of health behavior. PMT indicates that individuals can formulate their protective behavior based on threat and coping appraisals that appear to explain protective motivation of users in the mHealth context. Although the PMT is widely used, threat and coping appraisal as a certain sequence of cognitive appraisal process remains unknown. Furthermore, with gender being one of the most fundamental individual characteristics, previous investigations discovered that males and females had varying decision-making processes (Shao, Zhang, Li, & Guo, 2019; Venkatesh, Morris, Davis, & Davis, 2003). In technology's adoption or rejection context, gender is the most influential demographic factor (Alam, Hoque, Hu, & Barua, 2020). In numerous study contexts, several investigations showed gender differences, including information disclosure in Location-based service (LBS) behaviors (Li, Mou, Ye, Long, & Huang, 2021), Social network sites (SNS) continuance (Krasnova, Veltri, Eling, & Buxmann, 2017), online buying (Zhang, Shao, Li, & Feng, 2021) and computer security behavior (Verkijika, 2019). Healthy systems are not gender neutral, gender differences cannot be ignored in the mHealth app use context.

Given all these considerations, this study attempted to explain how threat and coping appraisals of PMT support users' continuance intention of using mHealth apps, and how gender affects the appraisal process of PMT. Therefore, based on PMT and gender differences, this study constructed a theoretical model that considered the threat and coping appraisals as a sequence and compared the variations in the appraisal process of PMT across genders.

We adopted an online survey to obtain data from 345 users of Spring Rain Doctor (a common mHealth app), and used a structural equation model to evaluate hypotheses. This study has numerous contributions. First, this study extends the understanding of the appraisal processes of PMT as a certain sequential process. Second, it supports the literature on the mHealth app's continuance by establishing an understanding of the influences of health-related factors on continuance intention and the moderating function of gender on these impacts. Finally, a deeper understanding of how the appraisal process is contingent on gender not only further validates the impact of gender disparities on users' continuance intention, but also provides companies with insights that effectively improve their products and services.

2. Literature review

Relevant studies on the factors and mechanisms of continuance intention of mHealth apps have gradually increased. Table 1 summarizes the academic literature on mHealth apps

Authors	Theory	Methodology	Key influencing factors
Beldad and Hegner (2018)	Technology acceptance model (TAM)	Empirical study	Perceived ease of use, perceived usefulness, injunctive social norm, trust, social influence and heath valuation
Cho (2016)	Post-acceptance model (PAM), technology acceptance model (TAM)	Empirical study	Perceived usefulness, perceived ease of use, confirmation and satisfaction
Yuan *et al.* (2015) and Woldeyohannes and Ngwenyama (2017)	Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)	Empirical study	Performance expectancy, hedonic motivations, price value, and habit; effort expectancy, social influence, and facilitating conditions
Huang and Ren (2020)	Technology Acceptance Model (TAM) and human-technology interaction perspective	Empirical study	perceived usefulness, perceived ease, perceived enjoyment, technological functions, exercise self-efficacy
Song *et al.* (2021)	Expectation-Confirmation Model (ECM), IS success model (ISCM)	Empirical study	Perceived usefulness, User satisfaction, perceived health status, information quality, system quality and service quality
Kumar, Singh, Pereira, and Leonidou (2020)	Expectation confirmation Model (ECM), technology Acceptance Model (TAM)	Empirical study	Satisfaction, confirmation, perceived ease of use, perceived usefulness, trust, social influence, perceived service quality, perceived privacy and security
Wang *et al.* (2021)	Expectation-confirmation model (ECM), self-determination theory (SDT)	Empirical study	Intrinsic motivation, satisfaction, confirmation, perceived usefulness
Hsiao and Chen (2019)	Expectation-confirmation model (ECM) and characteristics of individual, technology and task	Empirical study	Perceived usefulness, technology maturity, individual habits, task mobility and user satisfaction
Akter *et al.* (2013b)	Expectation-confirmation theory (ECM), service quality and consumer trust	Empirical study	Perceived usefulness, perceived service quality, perceived trust, confirmation, satisfaction
Zagita, Handayani, and Budi (2019)	Technology Acceptance Model (TAM), post-acceptance model (PAM), and Elaboration Likelihood Model (ELM)	Empirical study	Perceived usefulness, perceived ease of use, confirmation, satisfaction, trust, doctors' information quality and service quality, and applications' reputation and institution assurance
Zhang *et al.* (2018)	Elaboration likelihood model (ELM), Expectation-confirmation theory (ECM)	Empirical study	Perceived e-health literacy, scrutinizing information, system quality, trust and satisfaction
Chen, Yang, Zhang, and Yang (2018)	Elaboration likelihood model (ELM)	Experiment	Perceived usefulness, trust, doctor's service quality and information quality, app's reputation and institution assurance

(*continued*)

Table 1.
Summary of previous studies on continuance intention of mHealth apps

Authors	Theory	Methodology	Key influencing factors
Wu (2018)	IS success model (ISCM)	Empirical study	Perceived usefulness, social support, information quality, service quality, patient satisfaction
Hossain and Alamgir (2016)	IS success model (ISCM)	Empirical study	Platform quality, quality of advice, interaction quality, perceived value and user satisfaction
Akter *et al.* (2010)	SERVQUAL	Empirical study	Platform quality, interaction quality and outcome quality
Kim *et al.* (2019)	SERVQUAL	Case study	Engagement, content quality, reliability, usability and privacy
Meng *et al.* (2022)	Trust theory	Empirical study	Affective and cognitive trust, technology and health anxiety
Birkmeyer *et al.* (2021)	Technology acceptance model (TAM)	Empirical study	Perceived disease threat, health consciousness, attitude towards mHealth, personalization, interaction, mobile app design, social networking, satisfaction and word of mouth
Li *et al.* (2019) and Gupta *et al.* (2021)	Expectation confirmation theory and social comparison theory perspective	Empirical study	Activity amount ranking, activity frequency ranking, confirmation
Luo *et al.* (2021)	Protective motivation theory (PMT), network externalities	Empirical study	Perceived vulnerability, self-efficacy, response efficacy, direct and indirect network externalities, attitude towards mHealth
Yan *et al.* (2021)	Expectation Confirmation Theory (ECT), technology acceptance model (TAM) and flow theory	Empirical study	Perceived usefulness, perceived ease of use, subjective norms, flow experience, health consciousness, behavioral change techniques
Lee and Cho (2017)	Uses and gratification theory	Empirical study	Recordability, networkability, credibility, comprehensibility and trendiness significantly predict user CI for diet/fitness apps
Wu *et al.* (2022)	Extended expectation confirmation model (ECM) with IT identity and mindfulness	Empirical study	Expectation-confirmation, perceived usefulness, user satisfaction, IT identity and IT mindfulness
Xiao *et al.* (2021)	Valence Framework	Empirical study	Perceived risk (physical risk, social risk and privacy risk), perceived value (convenience value, utilitarian value, social support value and monetary value)

Table 1.

continuance. The most frequent used theories involving Information systems (IS) success model (ISCM), Extended unified theory of acceptance and use technology (UTAUT2), TAM, Elaboration likelihood model (ELM) and Expectation-Confirmation Model (ECM). Some studies extended these theories by integrating other perspectives. For instance, Huang and Ren (2020) extended TAM from human-technology interaction perspective, testing the role of technological functions and exercise self-efficacy in users' intention to continue in the context of using fitness app. Li, Liu, Ma, and Zhang (2019) and Gupta, Dhiman, Yousaf, and Arora (2021) combined ECM and social comparison theory, believing that expectation confirmation is the internal driving force and social comparison is the external driving force. Wang *et al.* (2021) also combined ECM and self-determination theory (SDT) and found that intrinsic motivation of using mHealth apps also had a significant impact on satisfaction and continuance intention. Considering information technology (IT)–specific traits, Wu, Zhou, Wang, Huang, and Yuan (2022) integrated ECM with IT identify and IT mindfulness and found that they are associated with consumers' continuance intention with mHealth technology. In addition, relevant literature with different theories has also begun to increase, such as trust theory (Meng, Guo, Peng, Ye, & Lai, 2022) uses and gratification theory (Lee & Cho, 2017), Service Quality (SERVQUAL) (Akter, D'Ambra, & Ray, 2010; Kim *et al.*, 2019), valence framework (Xiao, Mo, & Huang, 2021) and flow theory (Yan, Filieri, Raguseo, & Gorton, 2021).

Although these studies have provided insights into users' continued intention to use mHealth apps, only few studies begin to take health-specific factors of mHealth services into consideration. For example, Luo *et al.* (2021) and Liu, Qin, Ma, Pian, and Mou (2022) investigated the influence of perceived threat and coping appraisals in PMT on continued use in eHealth, while they ignored the sequential process of threat and coping appraisals. In addition, gender, as an important social stratifier which affects health system needs, experience and outcomes, has not been effectively valued in the continuous use of mHealth apps context. Thus, more academic studies are needed to understand the sequential process of threat and coping appraisals and the moderated role of gender.

3. Theoretical foundations and research hypotheses

3.1 PMT

PMT is developed based on the health belief model and was originally employed to describe how people react to anxiety by making the change that benefits their health (Rogers, 1983). PMT has been extensively used in examining the change in health behaviors (Anderson & Agarwal, 2010a; Guo, Han, Zhang, Dang, & Chen, 2015). The behavioral changes are measured by a cognitive appraisal process, such as threat and coping appraisal (Rogers, 1983). Threat appraisal is the evaluation of unhealthy behaviors or diseases, involving perceived severity and perceived vulnerability (Rogers, 1983). Perceived vulnerability is an individual's subjective judgment about the likelihood that he or she develops a disease, whereas perceived severity is an individual's judgment of the unhealthy behavior's severity. Perceived vulnerability and perceived severity are frequently combined as perceived threats (Turner, Rimal, Morrison, & Kim, 2006).

The coping appraisal is an evaluation of an individual's ability to cope with and avoid hazards, including response efficacy, self-efficacy and response cost. Response efficacy is defined as the degree to which an individual perceives the effectiveness of a protective action taken to reduce hazard, self-efficacy refers to confident degree in his or her ability to take protective actions and response cost refers to any costs perceived by the individual to be associated with taking protective actions (Floyd, Prentice-Dunn, & Rogers, 2000), such as money, time, effort, inconvenience and unpleasantness. The higher the perceived threat or levels of these efficacy variables, the higher the likelihood of protective behavior. However, the high response cost associated with conducting the protective actions may decrease the probability of implementing these behaviors. Summarily, an individual protective motivation could be stimulated by both threat and coping appraisals, which could then lead to an applicable adaptive response. Floyd *et al.* (2000) confirmed that protective behaviors could be considerably predicted and understood through the appraisals of threat and coping.

The PMT also has received confirmation in numerous contexts, like information security behavior (Menard, Bott, & Crossler, 2017) (Boss, Galletta, Benjamin Lowry, Moody, & Polak, 2015), sustainable consumption (Ibrahim & Al-Ajlouni, 2018), self-protective behavior in ride-sharing (Chen & Lu, 2021), security policy compliance (Moody, Siponen, & Pahnila, 2018), pro-environmental behavior (Chen, Dai, Zhu, & Xu, 2020a), self-protection in tourism (Wang, Liu-Lastres, Ritchie, & Mills, 2019) and acceptance of online health services (Mou, Shin, & Cohen, 2016). This stream of study has developed that threat and coping appraisals as parallel or disorganized sequences connect to users' protective intentions.

Tanner, Hunt, and Eppright (1991) posited an ordered PMT model, which considers an individual's cognitive appraisal process as a specific sequence, namely, threat appraisal coming first and coping appraisal after it. The more individuals believe they are vulnerable to a serious threat, the more motivated they will be engaged in coping appraisal (De Hoog, Stroebe, & De Wit, 2007). Lazarus (1968) showed the ordered nature inherent in threat and coping appraisals behaviors and described "... once threat appraisal occurs, information about feasible lines of coping is given the urgency or search processes important to coping are activated" (p. 197). Yet to the best of our knowledge, the mechanism accounting for the impacts of the two appraisals as ordered way on users' continuance intention to use mHealth apps has been totally untouched. Therefore, this study primarily focuses on the impacts of an ordered process for threat–coping appraisal on users' protective intention in the mHealth apps' context.

PMT is also applicable in the context of using mHealth apps. After a health risk accident, individuals generate self-protection motivation through using threat and coping appraisal, and then modify their behavioral to cope with health hazards.

First, perceived disease threat as a health-specific factor usually involves an individual's subjective judgment of the risk of getting a disease and the severity of the disease (Turner *et al.*, 2006). In this study, perceived disease threat was employed to denote the threat appraisal. The PMT suggests that the stronger the perceived threat of disease, the more likely an individual is to take health-related actions. Prior research has revealed substantial impacts of perceived disease threat on users' intentions to employ health-related actions (McClendon & Prentice-Dunn, 2001).

Following Tanner *et al.* (1991)'s suggestion, we posit that the relationship between the threat and coping appraisals ought to be orderly. Specifically, when an individual perceives a disease threat, assessing a given protective behavior (i.e. mHealth apps continued usage) would then be triggered. The assessment involves their ability to perform the behavior, the benefits from the behavior and the costs associated with the behavior. And the more they believe they are vulnerable to a serious threat, the more motivated they will be to engage in coping appraisal (De Hoog *et al.*, 2007). If the threat is considered as irrelevant or insignificant, the sequential coping appraisal is ignored. In contrast, when health risks are perceived as serious and relevant, individuals become fearful and their fear should motivate them to consider their coping options. Next, if they believe that their coping activities are efficient in reducing risk, they have more positive incentives to comply with them. In contrast, if users perceive these coping activities to be inefficient, they may feel that there is no point in complying with them. Some investigations in the context of information security provide some clues that threat appraisal causes coping appraisal (Johnston, Warkentin, & Siponen, 2015). Thus, we suggest that the coping appraisal mediates the effect of threat appraisal on the intention to adopt protective actions.

To be more specific, based on the stage model (De Hoog *et al.*, 2007), when individuals feel vulnerable to a severe disease, they will change their self-definitional belief that they are healthy, and consequently arouse defense motivation. Under such motivation, individuals adopt systematic message processing that is biased, but in a positive direction (Liberman & Chaiken, 1992). Individuals with defensive motivation will try to find information about the effectiveness of recommended protective behaviors in the process of information processing, so as to make them feel safe. Therefore, the cognitive biased processing will promote individuals to intentionally seek information about the effectiveness of protective behaviors. For example, they will use biased search information or evaluation information to support the effectiveness judgment of recommended protective behaviors. In other words, defensive motivation will lead to positive bias in the processing of protective behavior information, such as positive evaluation of response efficacy, self-efficacy and response cost of protective behavior in coping appraisals. In this study, continuance intention to use mHealth apps as a protective action, when individuals perceive a high health threat, they will make biased positive appraisals to the coping effect of this protective behavior, that is, high response efficacy and self-efficacy and low response cost. Furthermore, response efficacy, self-efficacy and the costs of adopting mHealth apps are considered as coping appraisal process. For a positive coping appraisal, it is necessary to believe that the protective action response is effective, that he or she has the ability to perform the action, and that the costs of adopting the action should not exceed the profit. An individual's contemplation of whether or not he or she will adopt a recommendation to protect against health threat through the continued use of mHealth apps. He or she will consider the capabilities of the mHealth apps solution and form a disposition toward the recommendation based on this appraisal.

Similarly, as individuals cognitively assess the ability to carry out a recommendation, self-efficacy is considered to be a determinant of intention to adopt the recommendation to address a threat (Rogers, 1983). Even if he or she believes that the advocated response is effective, the individual will still consider his or her ability to successfully use the mHealth apps to avoid a health threat (Anderson & Agarwal, 2010b; Johnston & Warkentin, 2010; Lewis, Agarwal, & Sambamurthy, 2003; Yoon & Kim, 2013).

Meanwhile, response cost in previous studies indicates a substantial impact on adaptive behaviors (Boss *et al.*, 2015; Lee, 2011). If it takes a lot of time, effort and money for users to adopt a recommended action, they hesitate to do it (Peace, Galletta, & Thong, 2003). The higher the cost individuals perceive, the less likely they are to adopt the mHealth apps.

Therefore, the following hypotheses are proposed:

H1. Response efficacy mediates the impact of perceived disease threats on continuance intention to employ mHealth apps.

H2. Self-efficacy mediates the impact of perceived disease threats on continuance intention to employ mHealth apps.

H3. Response cost mediates the impact of perceived disease threats on continuance intention to employ mHealth apps.

3.2 The moderating role of gender

In different decision-making situations, gender has been regarded as one of the important moderating variables (Venkatesh, Morris, & Ackerman, 2000; Zhou, Jin, & Fang, 2014b). For example, females and males vary in terms of service patterns, usage styles and preferences for specific applications in the online services context (Weiser, 2000). In the online shopping context, male and female have different shopping habits and different perceptions of web characteristics and online atmospherics (Zhang *et al.*, 2021), as they have varying needs structures and value numerous needs or expectations differently (Alderfer and Guzzo, 1979). In IT use contexts, gender can function in predicting IT use (Venkatesh & Morris, 2000).

Social role theory suggests that females and males behave differently because they are given different social roles in certain contexts (Eagly & Wood, 2013). Females tend to be social, people and process oriented, whereas males tend to be technical and task oriented (Venkatesh, Thong, & Xu, 2012). In particular, males tend to act decisively and independently that are demonstrated to function in task-oriented situations. In contrast, females prefer facilitation and friendly patterns of behaviors, which are shown to function in social- and people-centered environment (Lin & Wang, 2020). Taylor and Hall (1982) have discovered that males' behaviors are more utilitarian than that of females. Females tend to focus more on the effort's magnitude involved and the process of realizing their goals (Venkatesh *et al.*, 2012). Spence and Helmreich (1978) also proposed that females pay more attention to intrinsic motivators, whereas males are more concerned about extrinsic motivators.

Prior research has indicated that the "pragmatic" or task-oriented traits are more prevalent in the male group, making them easier to be affected by the utility and predicted performance (Venkatesh & Morris, 2000; Venkatesh *et al.*, 2012). For example, Zhou, Jin, and Fang (2014a) discovered that males are prone to use a special technology to realize instrumental needs and obtain utilitarian advantages. The most direct advantage of using mHealth apps is to limit health threats during health management. Response efficacy can be thought of as outcome prediction of protective behavior (Chen & Lu, 2021), representing a utilitarian value in health management (i.e. reducing disease threat). It may generate more positive behavioral intention among male users. Thus, this study suggests the following hypothesis:

H4a. The impact of response efficacy on continuance intention to use mHealth apps is stronger for males than for females.

Compared with males, females are more sensitive to threat-related stimuli and show more negative effects (Garbarino & Strahilevitz, 2004) and are more likely to develop positive attitudes to protect themselves after gaining how to do so (Verkijika, 2019). Generally, females' levels of security self-efficacy are lower (Anwar *et al.*, 2017), so an increase in self-efficacy for females might have a greater impact on their protective behaviors. This is especially predicted in females who believe the disease threat's severity is high for them, so if they have the know-how to do so, they will be more likely to try to guide themselves. However, even though males generally have higher mHealth self-efficacy, it was also generally found that individuals who have high self-efficacy might not always consider security measures. This outcome can be more obvious among males as they tend to think that the disease threat might not have severe consequences for them, whereas females perceive the disease threat's severity as high (Verkijika, 2019). So even if males know what to do, they might not be motivated to adopt a good protective behavior, as they perceive the disease threat is not serious. Following the above discussion, this investigation hypothesizes that:

H4b. The self-efficacy's impact on continuance intention to use mHealth apps is stronger for females than for males.

Furthermore, response cost denotes perceived costs associated with taking mHealth apps. Examples of such perceived costs involve challenges, cost, time, effort, inconvenience and complexity (Floyd *et al.*, 2000). Social role theory suggests that females are more process-oriented and therefore perceived ease of use is always to be more important for females than for males (Venkatesh & Morris, 2000). However, females are more concerned about economic advantages than males (Eagly & Wood, 2013), more sensitive to the price and rewards of products and services, and more cost-conscious than males (Venkatesh *et al.*, 2012). Thus, the higher level of response cost, the more hesitant users are to employ mHealth apps as the recommended protective actions. Therefore, the study proposes the following hypothesis:

H4c. The response cost's impact on continuance intention to use mHealth apps is stronger for females than for males.

According to the above discussion, a conceptual model is constructed (see Figure 1). This model has explained a sequence influence mechanism of threat and coping appraisals on continuance intention, as well as the moderating mechanism of gender.

Following the previous study, we regulate numerous variables that potentially affect the continuance intention to employ mHealth apps, such as annual income (Feng, Li, & Lin, 2021) and health condition (Meng *et al.*, 2022). In addition, the recommended protective action in this study was technology use oriented, that is, the continuance intention to use mHealth apps. In determining how users will react to technology use, age, education and social influence play an important role (Alam *et al.*, 2020; Venkatesh *et al.*, 2012). Thus, the study considers age, education and social influence as control variables.

4. Research methodology

4.1 Data collection

To empirically evaluate the proposed model and hypotheses, an online questionnaire survey is employed to obtain data via www.sojump.com, an electronic questionnaire website. Sojump with clients covering 90% of universities and more than 30,000 enterprises has become the largest online survey service platform in China (Shen, Li, & Sun, 2018).

We collected data from the users of Spring Rain Doctor, which is a popular mobile doctor-patient communication platform in mainland China (Chen, Lan, Chang, & Chang, 2020b). To ensure that the respondents are users of Spring Rain Doctor, we included a prescreening question to ask respondents if they had used Spring Rain Doctor. Only those who answered "yes" were asked to continue answering the questionnaire. In total, 368 questionnaires were collected. Questionnaires with the same answers to all questions or completed within a short period of time were treated as invalid and removed. 345 valid questionnaires were retained for analysis.

Table 2 describes the overall sample's demographics, wherein 47.9% are male and 52.1% are female. Most respondents (50.7%) were 26–35 years of age. Approximately 74.8% of the respondents had a bachelor's degree or above, and approximately 86.6% were in healthy or sub-healthy conditions. In particular, we compared our sample with authoritative investigations in China with respect to demographic variables such as age, gender and income. The results show that the demographic characteristics of the respondents are basically matched with the actual users of Spring Rain Doctor (Analysys, 2021), indicating that our respondents is representative of the actual mobile health users of Spring Rain Doctor.

4.2 Measurement

The measurement items were derived from previous studies and adjusted appropriately for the context of this study. Each item was measured using a 7-point Likert scale ranging from 1 "strongly disagree" to 7 "strongly agree". Table 3 shows the measurement items, sources and

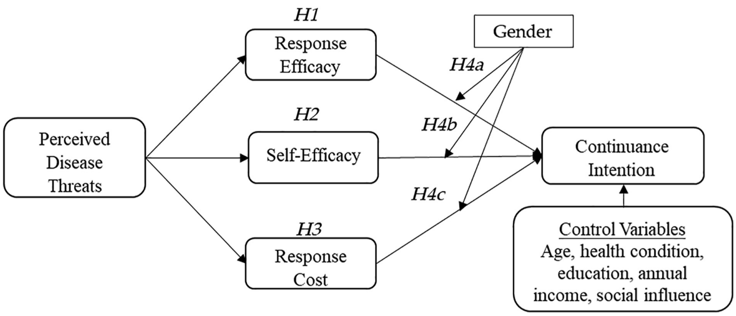


Figure. 1.
Research model and hypotheses

Table 2.
Descriptive statistics of samples

Items	Types	Frequency	Percentage (%)
Gender	Male	165	47.9
	Female	180	52.1
Age (years)	18–25	69	20.0
	26–35	175	50.7
	36–45	66	19.1
	46–65	35	10.1
Education level	High school and below	36	10.4
	Junior college	56	16.2
	Bachelor's degree	190	55.1
	Master's degree and above	63	18.3
Health condition	Healthy	146	42.3
	Sub-healthy	153	44.3
	Minor illnesses	30	8.7
	Chronic diseases	16	4.6
Annual income	Under 50,000	95	27.5
	50,000–100,000	116	33.6
	100,000–200,000	106	30.7
	200,000–300,000	24	7.0
	300,000 and above	4	1.2

factor loading. To ensure the data's accuracy and scientific validity, we invited two professionals in the information system to translate the questionnaire from English to Chinese and numerous postgraduate students to review the translation. Based on their feedback, we adjusted the questionnaire. At last, we invited 20 graduate students who employed "Spring Rain Doctor" mHealth apps to pretest the questionnaire and revised it again accordingly.

4.3 Analysis and results

Structural equation modeling (SEM) was employed to test the research model. In particular, SmartPLS 3.2 was chosen to do statistical analysis for two reasons: one is that the study's focus was to assess individuals' intentions to continue using mHealth apps. Since Partial Least Squares (PLS) optimizes the endogenous constructs' explained variance, it is suitable for this research (Hair, Sarstedt, Ringle, & Mena, 2012). Another is that the results of the Shapiro–Wilk tests for our measurements were significant, indicating that these measurements do not fit a normal distributed. PLS has no requirement on whether the data is normally distributed data (Hair, Hult, Ringle, & Sarstedt, 2016) following a two-step analysis strategy, the measurement model is investigated first, followed by the structural model.

4.3.1 Common method bias analysis. This study employed the single-factor extraction test as suggested by Harman (1976) to identify common method bias (CMB). When a principal factor explains more than 50% of the variance of the instrument variables, CMB is then determined to exist (Podsakoff & Organ, 1986). A principal component analysis was performed for all measurement items, and 6 factors were obtained and explained 77% of the variance, among which the first single factor accounted for only 42% of the variance, which was less than the threshold value 50%, indicating that CMB was not serious (Podsakoff & Organ, 1986).

4.3.2 Measurement model analysis. The testing of measurement models involves reliability and validity tests. Reliability is employed to determine whether the variables scale's findings are reliable, which can be observed through composite reliability (CR) value and Cronbach's alpha value. Validity involves convergent and discriminant validity. Convergent validity

Constructs	Items	Loading	References
Perceived disease threats (Cronbach's alpha = 0.849)	PDT1. I find I am at risk for serious illness	0.822	Huang (2010)
	PDT2. I think it's possible that I will fall into serious illness in the future	0.917	
	PDT3. I think it's possible that I will suffer from a disease	0.883	
Self-efficacy (Cronbach's alpha = 0.792)	SE1. Using the mHealth apps is easy for me	0.842	Johnston and Warkentin (2010)
	SE2. The mHealth apps are easy to use	0.810	
	SE3. I can use the mHealth apps effortlessly	0.864	
Response efficiency (Cronbach's alpha = 0.789)	RE1. The mHealth apps work for me in solving my issues	0.848	Johnston and Warkentin (2010)
	RE2. The mHealth apps are efficient for me in solving my problems	0.821	
	RE3. When employing the mHealth apps, my health issues are more likely to be guaranteed	0.846	
Response cost (Cronbach's alpha = 0.832)	RC1. There is too much overhead associated with the adoption of mHealth apps	0.883	Lee (2011)
	RC2. It takes a substantial amount of time and effort to be familiar with and employ mHealth apps	0.883	
	RC3. The use of the mHealth apps may cause distrustful relationships between doctors and me	0.829	
Social influence (Cronbach's alpha = 0.901)	SI1. Most of my friends are using the mHealth apps	0.929	Venkatesh *et al.* (2012)
	SI2. Most of my colleagues are using the mHealth apps	0.908	
	SI3. Most people in my circle of friends are using the mHealth apps	0.903	
Continuance intention (Cronbach's alpha = 0.865)	CI1. I intend to continue to use the mHealth apps	0.905	Bhattacherjee (2001)
	CI2. I will continue to use the mHealth apps	0.892	
	CI3. I would like to recommend the mHealth apps to others	0.865	

Table 3. Constructs, factor loadings and sources

tests the correlation degree between the question items and the corresponding variables and can be identified by the average variance extraction (AVE)'s value. Discriminant validity tests whether the question is more correlated with the corresponding variable than other constructs by comparing the square root of AVE value of each variable with the correlation coefficients between the variables.

Table 4 displays that CR values of all constructs are greater than 0.7, and Table 3 shows that the factor loadings of all items and Cronbach's alpha values are between 0.789 and 0.901. All these indicate that the measurement model has good reliability (Fornell & Larcker, 1981). The AVE values of all constructs range from 0.703 to 0.834, indicating a good convergent validity. The square root of AVE values of each variable (diagonal values) is larger than the correlation coefficients between the variables (see Table 4), demonstrating a good discriminant validity.

4.3.3 Structural model analysis for the full sample. SEM was employed to test the explanatory power and the path coefficients of the research model. The statistical significance of the parameter estimates was tested by bootstrapping procedure method (Temme, Kreis, & Hildebrandt, 2010). Figure 2 and Table 5 present our analysis findings.

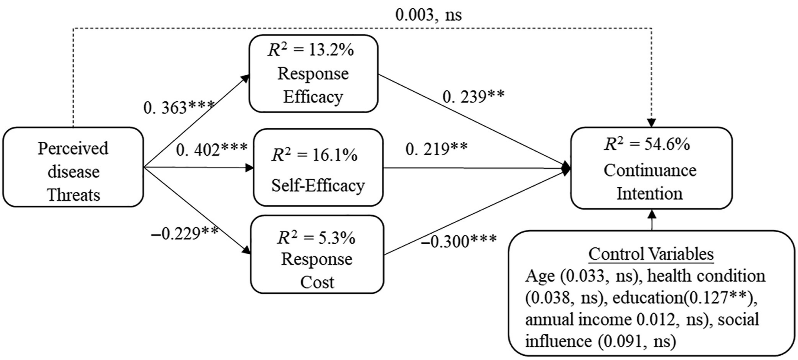
As presented in Figure 2, the full sample's model test findings revealed that perceived disease threats positively influences response efficacy ($\beta = 0.363, p < 0.001$) and self-efficacy ($\beta = 0.402, p < 0.001$). In contrast, perceived disease threats negatively influences response cost ($\beta = -0.229, p < 0.001$). Then, response efficacy ($\beta = 0.239, p = 0.001$) and self-efficacy ($\beta = 0.219, p = 0.003$) positively affect continuance intention, but response cost ($\beta = -0.300, p < 0.001$) negatively influences continuance intention.

To investigate the assumption that threats and coping appraisals are orderly, we assessed the mediating function of response efficacy, self-efficacy and response cost (see Table 5). The findings revealed that the indirect effects of perceived disease threats on continuance intention through response efficacy ($\beta_{PDT \rightarrow RE \rightarrow CI} = 0.087$, S.E. = 0.029, 95% CI: [0.037, 0.137]), self-efficacy ($\beta_{PDT \rightarrow SE \rightarrow CI} = 0.088$, S.E. = 0.036, 95% CI: [0.028, 0.147]) and response cost ($\beta_{PDT \rightarrow RC \rightarrow CI} = 0.069$, S.E. = 0.020, 95% CI: [0.035, 0.102]) are significant in the full sample, supporting H1, H2 and H3.

Table 4.
A correlation matrix, CR, AVE and square root of AVE values

Constructs	AVE	CR	Correlations 1	2	3	4	5	6
1. Perceived disease threats	0.765	0.907	*0.875*					
2. Self-efficacy	0.704	0.877	0.402	*0.839*				
3. Response efficiency	0.703	0.877	0.363	0.605	*0.838*			
4. Response cost	0.749	0.899	−0.229	−0.528	−0.582	*0.865*		
5. Social influence	0.834	0.938	0.244	0.464	0.485	−0.421	*0.913*	
6. Continuance intention	0.788	0.918	0.273	0.584	0.622	−0.626	0.447	*0.887*

Note(s): The AVE's square root is shown in italic as the diagonal



Note(s): *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed); ns (nonsignificant)

Figure. 2.
Results of structural model analysis for the full sample

Table 5.
Results of the indirect impacts of perceived disease threats on continuance intention

Hypotheses	Mediators	Indirect effect coefficients	Bias-corrected 95% confidence intervals (CIs) Lower	Upper
H1	Response efficacy	0.087 (0.029)	0.037	0.137
H2	Self-efficacy	0.088 (0.036)	0.028	0.147
H3	Response cost	0.069 (0.020)	0.035	0.102

Regarding the research model's explanatory power, the R^2 reveals that the model explains 54.6% of the variance in continuance intention, showing that the model fits well and has a high predictive ability. Additionally, the computed standardized root mean residual (SRMR) of 0.055 is less than the recommended cut-off value of 0.08, demonstrating that the model had a good fit (Hair, Marko, Ringle, & Gudergan, 2018).

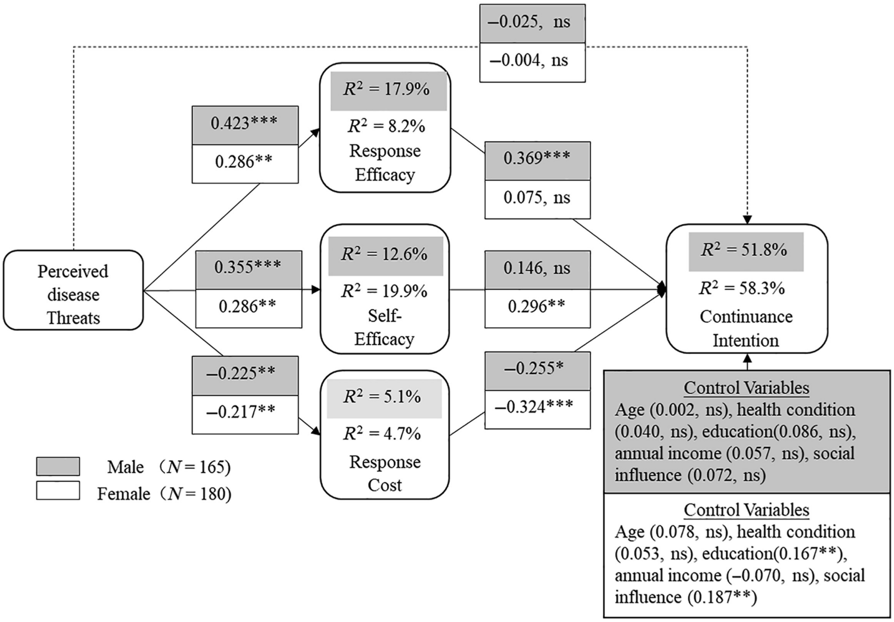
4.3.4 Multigroup measurement invariance test. For subsequent comparisons between groups, following the procedure of the measurement invariance of composite models (MICOM) (Hair, Hult, & Ringle, 2014), we further evaluated the measurement invariance among male and female groups employing SmartPLS 3.2. Measurement invariance tests involve configural invariance and compositional invariance. First, as this research employed the same measurement questions in data collection and the same approaches in data analysis, the measurement of variables between male and female groups agrees with the configural invariance. Second, the correlation coefficients of all variables' between-group scores fell into a 95% confidence interval based on the permutation algorithm (perceived disease threats: correlation coefficient = 1.000, 95% CI = [0.992,1]; response efficacy: correlation coefficient = 0.999, 95% CI = [0.997,1]; self-efficacy: correlation coefficient = 0.999, 95% CI = [0.997,1]; response cost: correlation coefficient = 0.999, 95% CI = [0.998,1]; continuance intention: correlation coefficient = 1.000, 95% CI = [0.999,1]) and social influence: correlation coefficient = 0.999, 95% CI = [0.998,1], indicating the measurement of variables between the male and female group agrees with the compositional invariance. Thus, the measurement invariance between male and female groups is confirmed.

4.3.5 Multiple group analysis. Figure 3 shows that the male and female group samples are used to test the moderating impacts. The path coefficients in varying gender groups changed to different degrees. To further determine the importance of coefficient changes, the $t_{spooled}$ statistics and corresponding p-values of the path coefficients of male and female groups are computed (Ahuja and Thatcher, 2005), as indicated in Table 6. The findings show that the impact of response efficacy on continuance intention is significantly stronger in male group than in female group ($\beta_{male} = 0.369, p = 0.000; \beta_{female} = 0.075, p = 0.413; t_{spooled} = 30.795, p = 0.000$), supporting H4a, whereas the impact of self-efficacy on continuance intention is significantly weaker in male group than in female group ($\beta_{male} = 0.146, p = 0.160; \beta_{female} = 0.296, p = 0.001; t_{spooled} = 14.355, p = 0.000$), supporting H4b. In the case of response cost, the findings show that females have a greater negative effect on continuance intention than males ($\beta_{male} = -0.255, p = 0.013; \beta_{female} = -0.324, p = 0.000; t_{spooled} = 6.638, p = 0.000$), supporting H4c.

4.3.6 Moderated mediation test as post-hoc analysis. Additionally, we further compared the mediating functions of response efficacy, self-efficacy and response cost across gender. Based on path coefficients in varying gender groups, smartPLS can provide the mediating path coefficient and p-value (see Table 7). Then we followed on the formula derived from Keil *et al.* (2000) to compute the $t_{spooled}$ value of the differences in the mediating path coefficient for the male and female groups. As shown in Table 7, we discovered that the impacts of perceived disease threats on continuance intention through self-efficacy ($t_{spooled} = 16.328, p = 0.000$) and response cost ($t_{spooled} = 4.234, p = 0.000$) are significantly higher for females than for males, whereas the impacts of perceived disease threats on continuance intention through response efficacy ($t_{spooled} = 31.987, p = 0.000$) are considerably higher for males than females.

5. Discussion

This study proposes that PMT is a crucial mechanism of personal protective behavior in mHealth apps using contexts. We confirm that PMT can also describe the ordered mechanisms of individuals' protection intention in mHealth apps using context, that is, the ordered impacts of threats and coping appraisals on continuance intention. Furthermore, the ordered impacts are found to be moderated by gender.



Note(s): *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed); ns (nonsignificant)

Figure. 3.
Test model (male and female group samples)

First, grounded on the PMT, we theoretically explain and empirically investigate the mediating function of coping evaluation, including efficacy and cost of response, self-efficacy, on users' continuance intention to employ mHealth apps. The findings of this study offer strong support for our hypotheses (i.e. H1, H2, and H3) and demonstrate that the ordered relationships between threatening and coping appraisal of PMT exist in the mHealth app's context. The proposed mediating model contributes to the existing study by indicating the crucial mediated function of coping appraisal between threatening appraisal and protective actions. More specifically, when individuals perceive that they are threatened by disease, they will be stimulated to first evaluate protective action, including efficacy and cost of response, self-efficacy, which represent various coping appraisals using healthcare apps. These evaluations have substantially influenced and offered a significant explanation for both the full sample and the two subsamples' intention to continue (i.e. males and females).

Second, and perhaps more importantly, we identify gender variances in the strength of the effect of various coping appraisals on continuance intention. Especially, response efficacy is more significant for males in terms of formulating their protection intention. Moreover, for the male users, the path coefficient of response efficacy on continuance intention is much greater than those of self-efficacy and response cost, so it has the strongest effect on improving male users' continuance intention. This agrees with the finding of Chen and Lu (2021) that response efficacy has a stronger positive influence on protection motivation with mHealth apps for males than females.

Conversely, this study illustrates that the reaction to self-efficacy and response cost of female users is more favorable than males. This is congruent with the arguments of Verkijika (2019), who discovered that females tend to gain more from protective actions' self-efficacy than males. Moreover, as discovered by Venkatesh *et al.* (2012), females are probably to more focus on the prices of products and services and pay more attention to the costs than males.

Table 6. Comparison of path coefficient between male and female groups

Hypotheses	Paths	Males		Females		Path differences	
		Coefficients	p-value	Coefficients	p-value	$t_{spooled}$	Hypotheses
H4a	Response efficacy → Continuance intention	0.369	0.000	0.075	0.413	30.795^{***}	Supported
H4b	Self-efficacy → Continuance intention	0.145	0.160	0.296	0.001	14.355^{***}	Supported
H4c	Response cost → Continuance intention	−0.255	0.013	−0.324	0.000	6.638^{***}	Supported

Note(s): ***$p < 0.001$. The formula for computing the $t_{spooled}$ significance of the differences in the path coefficients for the various subgroup samples is derived from Keil *et al.* (2000) (see Appendix for details)

This study also discovers that although response cost considerably impacts continuance intention for both the male and female subsamples, the impact strength of females is significantly higher than that of males.

Third, a post-hoc analysis of the gender variances in the indirect impact strengths of threatening appraisals on continuance intention through different coping appraisals further indicates that there are various mechanisms between females and males. When facing threats, males and females tend to focus on different coping appraisals. Males will enhance continuance intention through response efficacy appraisal, whereas females will pay more attention to self-efficacy and response cost appraisals, therefore improving the continuance intention. Overall, the findings of this study further support the significance of gender in mHealth apps research. The theoretical and practical contributions of this study are as follows.

5.1 Theoretical implications

First, we develop a theoretical link between health-specific factors and continuance intention. Specifically, perceived disease threats as threat appraisal, response efficacy, self-efficacy and response cost as coping appraisal, which are described as users' protection motivation, thereby improving protective behavior, i.e. continuance intention to employ mHealth apps. Accordingly, in mHealth apps use context, users' continuance intention should not only be motivated from the available mHealth application, but should include the basic health needs of the users.

A second contribution is that this study suggests that the relationship between threat and coping appraisals should be orderly. Previous studies majorly considered threat and coping appraisals as parallel relationships and examined their effect on individuals' protective behavior from the cognitive appraisal process. But the ordered relationship between them remains uninvestigated. In mHealth apps use context, individuals' perception of disease threat first stimulates their evaluation for protective behaviors to be taken, rather than directly taking the protective behavior. In particular, we discover that coping appraisal completely mediates the relationship between perceived disease threats and sustained use intention of mHealth apps.

The third contribution of this study is that it extends the line of research by proposing that the effects of these coping appraisals on continuance intention are contingent on users' gender. Given varying need structures and decision-making process in using mHealth apps, males and females may respond differently to the same set of coping appraisals, which then produce different level of continued use of mHealth apps. Generally, there are gender variances in the extent to which coping appraisals of a particular group influence continuance

Table 7. Comparative results of mediating effects of male and female groups

Pathway	Male Coefficients	Male p-value	Female Coefficients	Female p-value	Path differences t_{spooled}
Perceived disease threats → Response efficacy → Continuance intention	0.156	0.001	0.022	0.427	31.987***
Perceived disease threats → Self-efficacy → Continuance intention	0.052	0.270	0.132	0.003	16.328***
Perceived disease threats → Response cost → Continuance intention	0.057	0.046	0.070	0.013	4.234***

Note(s): ***$p < 0.001$. The formula for computing the t_{spooled} significance of the differences in the path coefficients for the various subgroup samples is derived from Keil *et al.* (2000) (see Appendix for details) intention. For males, response efficacy appears to have a more significant impact on the sustained usage of mHealth app than the females. This implies that when males want to use mHealth apps, they are more concerned about the outcome of using the mHealth app. In contrast, female users' continuance intention is mainly predicted by response cost, followed by self-efficacy, meaning that females are more concerned about the process of using the mHealth app. The post-hoc analysis revealed that the mediated function of self-efficacy is only important for females and not for males, but the mediated function of response efficacy is only crucial for males and not for females. Although the mediated function of response cost is found to be substantial for both males and females, the impact strength of females is substantially higher than that of males. Thus, this study is beneficial to extending the gender variances literature to a crucial research field, that is, mHealth app user behavior and suggests that investigators of mHealth app usage should consider mHealth app user gender in their study.

5.2 Practical implications

There are a set of insights into the development and management of mHealth apps for practitioners. First, the protection motivation could drive continued use intention of mHealth app, indicating that mHealth app developers should take suitable techniques to motivate users' threat and coping appraisals. Since mHealth apps are health-related systems, mHealth app developers need to leverage health-related risks and advantages to improve user continuance intention with mHealth apps. However, practitioners should know that in mHealth apps use context, threat appraisal does not directly stimulate users' protection intention, but coping appraisal does. An effective threat appraisal generally inspires coping appraisal that involves decreasing response costs while increasing self-efficacy and response efficacy.

In terms of coping appraisal, this research proposes that efficacy and cost of response and self-efficacy are simultaneously but with different weights key element determining users' protection intention. This has implications for the development and implementation of mHealth apps. To this end, mHealth apps should develop efficient health services to counter health risk accidents and convince users that these services are efficient. For instance, mHealth apps can generally depict the health services available on the app, thereby increasing users' perception of their efficacy. And, to some extent, the necessary engagement in the health services on mHealth apps ought to be simplified to minimize users' response cost and improve their self-efficacy. For example, mHealth apps should offer users with effective guidance or instructions on how to comply with health services.

The development and maintenance of mHealth applications are no "one-size-fits-all" method because different user groups – such as males versus females – have varied need structures. As for this research, we demonstrate that there are differences between male and female users' intentions to continue using mHealth applications, which involves how fulfilling various appraisals (i.e. the appraisal received from using mHealth apps) affects their intentions. Generally, this study suggests that, considering different categories of coping appraisal to improve user continuance intention, mHealth app developers ought to adopt various strategies for male and female users. Involving a significant amount of minimized response cost features into mHealth apps development might be an efficient approach in several cases, especially for improving continued use intention among female users who place a greater focus on response cost in using mHealth apps. Also, by offering an easy-to-use interface, easy-to-understand guidance or instructions and training on how to access health services, mHealth app developers could increase female users' self-efficacy. However, the different decision models and need structures may make the same approach less efficient for male users. In order to retain male users, it may be a good strategy for mHealth apps developers to put relatively more effort into response efficacy in mHealth apps development and management. For example, developers could highlight the utilitarian applications of mHealth apps (e.g. healthcare services and information, accurate and timely feedback) and emphasize the advantages of using mHealth apps. Our findings could therefore help mHealth apps to develop more focused and specific approaches to manage users' perceptions to improve their continuance intention.

5.3 Limitations and suggestions for future research

Although this research provides tangible findings on users' continued use intention of mHealth apps, numerous constraints may point to future research directions. First, this study aims at users' intentions to continue using mHealth apps. Users' experience of use mHealth apps may impact their intention to continue using. In addition, though intentions are probably to impact actual behavior significantly, some factors, such as habits and switching costs, may also play crucial roles in predicting actual behavior. Thus these factors need to be considered in future research. Second, this survey was conducted on users of only a major Chinese mHealth app (Spring Rain Doctor), which is likely to generate selection bias. To increase the generality of the research's findings, future research could gather data from mHealth apps across numerous platforms or countries to investigate whether platform characteristics or culture influence PMT mechanisms in continuance intention. Third, this research only considers gender variances but does not examine other feasible moderating impacts. Future studies should also consider investigating individual differences from a broader perspective, such as age and experience (Weiser, 2000; Zhou *et al.*, 2014a) and health conditions. Fourth, emerging mHealth services such as wearables or smartwatches and accompanying apps, are increasingly recognized by users, and future studies ought to concentrate on these mHealth services. In addition, the privacy and data security issues of mHealth also deserve further study.

6. Conclusion

Drawing upon PMT and gender literature, this research designs a theoretical model to examine the influence of threat and coping appraisals moderated by gender on users' continued intention to use mHealth apps. The results fill a research gap by revealing an orderly relationship between threat and coping appraisals. The influence of threat appraisal (i.e. perceived disease threats) on protective behavior (i.e. continuance intention to use mHealth apps) will be achieved through various coping appraisals. Furthermore, the study also builds the boundary conditions for the research model by observing the moderating effect of gender. To be specific, this study shows that males prefer results-related decision mechanisms (i.e. response efficacy), while females focus more on process-related decision mechanisms (i.e. self-efficacy and response cost). These findings contribute to a deeper understanding of the potential impacts of coping appraisal on protective behaviors of different users.

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Appendix

The formula for testing the significance of differences in path coefficients is $S_{pooled} = \sqrt{\frac{N_1-1}{N_1+N_2-2} \times SE_1^2 + \frac{N_2-1}{N_1+N_2-2} \times SE_2^2}$, $t = \frac{PC_1 - PC_2}{S_{pooled}\sqrt{\frac{1}{N_1}+\frac{1}{N_2}}}$, where S_{pooled} is the joint variance; t represents the statistical value of the degree of freedom $(N_1 + N_2 - 2)$; N_i represents the ith sample's sample size; SE_i represents the standard error of the path coefficient of the structural equation model for the ith *sample*; and PC_i denotes the path coefficient of the structural equation model for the ith sample.

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