USER PSYCHOLOGY AND BEHAVIOR REGARDING HEALTHCARE IT

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USER PSYCHOLOGY AND BEHAVIOR REGARDING HEALTHCARE IT

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Editorial: User psychology and behavior regarding healthcare IT

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Editorial on the Research Topic
User psychology and behavior regarding healthcare IT

In the last decade, it has been proven that healthcare information technology (IT) has significant potential for (1) improving service quality, (2) redistributing healthcare resources, (3) reducing healthcare cost, and (4) alleviating rural-urban health disparities (Agarwal et al., 2010; Goh et al., 2011; Mein Goh et al., 2016). During the COVID-19 pandemic, the public were able to efficiently manage their health conditions, receive social support, and attend remote health consultations through the use of relevant healthcare IT (Wood et al., 2019). Despite these benefits, several challenges are associated with the sustainable use of healthcare IT, including (1) physicians' under-contributions (Kim and Mrotek, 2016), (2) low patient engagement (Mirzaei and Esmaeilzadeh, 2021), and (3) poor membership retention and commitment in online platforms (Xing et al., 2018). Considering that healthcare IT involves personalization and human–computer interactions, researchers' sole focus on investigating factors related to the information technology side of healthcare IT is not sufficient enough to increase our understanding or to address these challenges. Accordingly, the objective of this Research Topic is to call for further investigations on user behavior regarding healthcare IT across multiple disciplines such as psychology, information systems, and human–computer interaction.

This Research Topic on "*User Psychology and Behavior Regarding Healthcare IT*" includes nine articles that address the abovementioned challenges related to the use of healthcare IT. These articles investigate information/knowledge sharing behaviors and usage behaviors, and incorporate (1) psychological rewards, (2) patients' trust, (3) health information privacy concerns, (4) social identity, (5) psychological distances, (6) prosociality, (7) anxiety, and other psychological factors in their research models. They include population samples of physicians, chronic patients, and the general population in the context of online health platforms and mobile health apps. More importantly, these articles offer valuable insights into user psychology and behavior regarding healthcare IT. Below, we summarize five of the nine articles:

Yao and Sheng examine the influence of psychosocial and technological factors on health information sharing adoption in the context of social sharing services. The authors develop a hypothesized model for health information social sharing adoption

(HISSA), integrating attitude beliefs, control beliefs, and normative beliefs. The model is empirically tested using a cross-sectional survey of 375 participants from China. The results show that the psychosocial factor normative beliefs is the most critical factor influencing user adoption intent. The proposed model also has practical implications for understanding the influences of these factors on user adoption behavior in a health context.

Tomczyk focuses on the psychometric properties of the German version of the information privacy concern (AIPC) scale, regarding the use of COVID-19 contact-tracing apps. Three-factor and four-factor models are empirically tested using a cross-sectional survey of 349 participants in Germany. The main findings include: (1) all factors in the four-factor model show good reliabilities and convergent as well as discriminant validities. The four-factor model is preferable compared with the three-factor model; (2) health information privacy concern is negatively associated with attitudes as well as use intention regarding contact-tracing mobile apps; and (3) factors measuring anxiety and personal attitude significantly overlap.

Zhang S. et al. attempt to understand the impact of previous first-aid experience on the online learning of first-aid knowledge and skills. Drawing on the construction level and prosociality theories, the authors consider individual psychological factors, and develop a research model for the psychological distances and prosociality mediating roles. The results show that previous first-aid experience positively impacts online first-aid learning intention. In addition, psychological distance from first-aid events, and prosociality, play significant mediating roles in the relationship between first-aid experience and learning intention. This study contributes to understanding first-aid learning intention by revealing the impact of individual psychological factors.

Guiomar et al. investigate the usability of the iACTwithPain platform in patients with chronic diseases and healthcare professionals. In a series of experiments, the authors examine participants' responses toward an intervention (video-animation, real-image video, and videoscribe animated video) while using the iACTwithPain platform. The main findings show that chronic patients prefer real-image video over animations or audio, whereas healthcare professionals are more attracted to the appealing and dynamic aspects of an animation. The intervention can significantly improve patient engagement and retention in the iACTwithPain platform, targeting the chronic patient market.

Zhang X. et al. investigate how patient visits and patient consultations influence physicians' online knowledge sharing, considering the contingent roles of physicians' online expertise and online knowledge sharing experience. Based on 6-month panel data from 45,449 physician-month observations in an online health platform in China, results indicate that both patient visits and patient consultations are positive regarding physicians' online knowledge sharing. Specifically, online expertise weakens the positive effects of patient consultations on physicians' online knowledge sharing. Moreover, the online knowledge sharing experience weakens the positive relationship between patient visits and physicians' online knowledge sharing, and enhances the positive relationship between patient consultations and physicians' online knowledge sharing.

Research on user psychology and behavior, in the context of healthcare IT, is lacking in terms of psychology, information systems, and human–computer interactions. Hence, this Research Topic addresses the gap in the literature by contributing to a better understanding of the influences of user psychology and behavior on the utilization of healthcare IT, and offers practical insights into how healthcare providers can improve the use of their healthcare IT.

Author contributions

FM: writing—original draft. XZ and LL: review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORIGINAL RESEARCH
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What Influences Physicians' Online Knowledge Sharing? A Stimulus–Response Perspective

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During the COVID-19 pandemic, online health platforms and physicians' online knowledge sharing played an important role in public health crisis management and disease prevention. What influences physicians' online knowledge sharing? From the psychological perspective of stimulus–response, this study aims to explore how patients' visit and patients' consultation influence physicians' online knowledge sharing considering the contingent roles of physicians' online expertise and online knowledge sharing experience. Based on 6-month panel data of 45,449 physician–month observations from an online health platform in China, the results indicate that both patients' visit and patients' consultation are positive related to physicians' online knowledge sharing. Online expertise weakens the positive effect of patients' consultation on physicians' online knowledge sharing. Online knowledge sharing experience weakens the positive relationship between visit of patient and physicians' online knowledge sharing, and enhances the positive relationship between patients' consultation and physicians' online knowledge sharing. This study contributes to the literatures about stimulus–response in psychology and knowledge sharing, and provides implications for practice.

Keywords: online knowledge sharing, stimulus–response, online health platforms, online expertise, psychology

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INTRODUCTION

The outbreak of COVID-19 has not only posed a severe threat to the healthy lives and wellbeing of people all over the world, but also caused significant challenges for health systems (Castelnuovo et al., 2020; Pan and Zhang, 2020; Luo et al., 2021). During the COVID-19 pandemic, online health platforms played an important role in public health crisis management and pandemic prediction (Zhao et al., 2020; Zhang et al., 2021). As a result of the rapid development of information technology (IT) and the huge demand for medical services, the delivery of health services on the internet has become increasingly popular (Hardey, 2001; Kvedar et al., 2014; Meng et al., 2021). Online healthcare can overcome geographic constraints and provide physicians with convenient access to information recipients (patients and their relatives); thus, an increasing number of physicians have been using online platforms to share their professional knowledge (Wu and Po, 2016; Zhang et al., 2019b). Physicians' online knowledge sharing has also been found to alleviate unbalanced allocations of health resources (Kim and Mrotek, 2016), which is important for China given its large population and uneven distribution of health resources.

Physicians' online knowledge sharing behavior has received extensive attention. Yan et al. (2016) applied the social exchange theory to investigate physicians' online knowledge sharing, categorized the influential factors into benefit and cost, and proposed a benefit vs. cost knowledge sharing model. Zhang et al. (2017b) explored online knowledge sharing from the perspective of motivation theory and found that reputation, reciprocity, knowledge self-efficacy, and altruism were positively related to physicians' online knowledge sharing intention. Meng et al. (2021) found that both online reputation and general knowledge sharing were positively related to specific knowledge sharing, and these relationships were moderated by patient involvement. However, few studies have explored physicians' online knowledge sharing from the perspective of patients. The benefits of an online medical platform mainly derive from patients' paid consultation, and patients' participation is important to improve the operational proficiency of the platform; therefore, we cannot ignore the effect of patients' participation on physicians' behavior. It is important to explore physicians' online knowledge sharing from the perspective of patients.

On an online medical platform, physicians' behaviors usually depend on patients and they are stimulated process in psychology (Liu et al., 2016; Yan et al., 2016). According to the psychological framework of stimulus–response, patients' visit and patients' consultation are important indicators reflecting the reputation and popularity of physicians (Yang et al., 2015b; Liu et al., 2016), which is stimulus for physicians. In response to this stimulus, physicians may share knowledge online. However, the existing literature has not explored the effect of patients' stimulus (patients' visit, patients' consultation) on physicians' response (online knowledge sharing of physicians). To fill this research gap, this study expects that patients' visit and patients' consultation will induce physicians' knowledge sharing. Accordingly, the first research question is presented as follows:

> *Q1: How do patients' visit and patients' consultation influence physicians' online knowledge sharing?*

User behavior regarding healthcare IT is not independent from its context (Zhang et al., 2021). To further investigate the boundaries of physicians' online knowledge sharing, this study also explores whether the effects of patient visit and consultation are contingent on physicians' online contexts. Physicians with high online expertise tend to have less freshness and interest in the platform; they will not pay attention to the stimuluses (patients' visit and patients' consultation) (Batson et al., 2002). Thus, online expertise may moderate the relationships between patients' visit and patients' consultation and physicians' online knowledge sharing. In addition, previous studies have proposed that past behavioral experience can shape the human decision-making process (Chiu and Huang, 2015). Physicians with rich experience of sharing health knowledge online tend to form habits, which are unconscious processes that can influence the effects of conscious processes on decision outcomes (Honkanen et al., 2005; Chiu et al., 2012; Chiu and Huang, 2015). When knowledge sharing becomes a habit, physicians will regularly share knowledge on the platform rather than rely on patients' visit and patients' consultation for knowledge sharing. In this vein, online knowledge sharing experience may moderate the effects of patients' visit and patients' consultation on physicians' online knowledge sharing. To explore the contingent factors that may affect the relationships between patients' visit, patients' consultation and physicians' online knowledge sharing, our second research question is presented as follows:

> *Q2: How are the relationships between patients' visit, patients' consultation and physicians' online knowledge sharing moderated by physicians' online expertise and online knowledge sharing experience?*

Drawing on the literature on the stimulus–response framework and knowledge sharing, a theoretical model associated with six hypotheses is developed. The hypotheses are tested using 6-month panel data with 45,449 physician–month observations from an online health platform in China. The results show that patients' visit and patients' consultation facilitate physicians' online knowledge sharing. Online expertise and online knowledge sharing experience hinder the positive effect of patients' visit on physicians' online knowledge sharing, while online knowledge sharing experience intensifies the positive effect of patients' consultation on physicians' online knowledge sharing.

This study also contributes to the literature in several ways. First, it contributes to the psychological literature on stimulus–response by introducing the stimulus–response framework to track the mechanism of physicians' online knowledge sharing. Based on the stimulus–response framework and literature of online knowledge sharing (Chen and Li, 2020; Meng et al., 2021), this paper uncovers the mechanism that patients' visit and patients' consultation benefit to physicians' online knowledge sharing. Second, this study contributes to the literature on knowledge sharing by identifying and verifying the stimulated factors of physicians' online knowledge sharing behavior from the perspective of patients. In response to calls that patients play a crucial role in value co-creation between physicians and patients (Van Oerle et al., 2016), our results reveal that both patients' visit and patients' consultation are important to physicians' online knowledge sharing. Third, the study contributes to the literature on online knowledge sharing and expertise by revealing the contingency effects of online expertise and online knowledge sharing experience in the process of physicians' online knowledge sharing. Behaviors of physicians and patients regarding healthcare IT is not independent from its context (Zhang et al., 2021), our empirical findings show that online expertise and online knowledge sharing experience indeed moderates the effects of patients' visit and patients' consultation on physicians' online knowledge sharing.

The structure of our paper is organized as follows. The Section 2 presents the theory background and hypotheses. The Section 3 introduces the research methodology. The Section 4 illustrates the results. The discussion, theoretical contributions, practical contributions, limitations and future research, and conclusion are discussed in Section 5.

THEORY BACKGROUND AND HYPOTHESES

Stimulus–Response Framework

The stimulus–response framework is a widely used psychological model (Reichl et al., 2006) that is introduced by Watson (1913). According to the framework, the complicated behaviors of humans are composed of stimulus and response (Watson, 1913; Giesen et al., 2020). Stimulus (S) refers to interior (individual) and exterior (environment) stimulation, while response (R) refers to the behavioral actions of humans in response to interrelated stimulus (Kim and Johnson, 2016; Luo et al., 2021).

The stimulus–response framework has been extensively applied in research into user online behaviors. Reichl et al. (2006) explored a charging mechanism for enhancing the quality of users' experience by applying the stimulus–response framework. Li and Chang (2012) constructed an integrated model based on the stimulus–response framework to explore the factors influencing users' continuous participation in virtual communities. The framework has also been used to investigate the relationship between online shopping festivals and consumer behavior (Xu et al., 2017; Liu et al., 2019). Chen and Li (2020) adopted the stimulus–response framework to explore the effect of product promotion strategies and atmosphere promotion strategies of consumers' perception on their willingness to participate in online shopping.

The framework of stimulus–response offers a visualized framework that enables researchers to study the reasons for, and processes of, physicians' online knowledge sharing behavior in online health communities (OHCs). Houston and Rothschild (1977) have classified stimulus into two categories. The first is stimulus from a specific object (e.g., patients' visit), which becomes a consideration for the individual. In the context of OHCs, as a result of information asymmetry and intangibility (Arrow, 1963; Parasuraman et al., 1985), patients visit physicians' homepages to obtain more information and assess whether the physicians meet their needs (Yang et al., 2015b). Physicians take the stimulus from patients' visit into account, and this influences the physicians' online knowledge sharing behavior. The second category is stimulus from the socio-psychology environment, which emphasizes the individual's expectation regarding the presence or absence of another person (Houston and Rothschild, 1977). Feedback from others can act as stimulus for sharing knowledge (Oo Tha, 2014). OHCs between physicians and patients are accompanied by a series of dynamic interactions (Guo et al., 2017) (e.g., patients' online consultation). Physicians provide health information during patients' online consultations, and in return they receive feedback, professional recognition, respect, bonuses, and incentives (Yang and Ju, 2016; Liu Y. et al., 2020). Therefore, patients' consultation stimulates physicians to respond to the expectation of patient presence, further influencing physicians' online knowledge sharing behaviors.

Behaviors of physicians and patients regarding healthcare IT is not independent from its context (Zhang et al., 2021). The effects of patients' visit and patients' online consultation on physicians' online knowledge sharing are dependent on context (e.g., online expertise and online knowledge sharing experience). Physicians with a high level of online expertise tend to realize strong online socialization through long-term sharing of knowledge as a result of their professional interests (Dodel and Mesch, 2018), which may affect the relationship between patients' visit, patients' online consultation and physicians' online knowledge sharing. If physicians have rich experience of knowledge sharing (e.g., a large number of published articles), online knowledge sharing may be a habit and may become a habitual behavior. As an unconscious process, habits can affect the conscious process of making decisions (Chiu and Huang, 2015). However, few studies have investigated the moderating effects of online expertise and online knowledge sharing experience on the relationship between patients' visit and patients' online consultation (S) and physicians' online knowledge sharing behavior (R). Online expertise and online knowledge sharing experience are crucial characteristics of physicians in OHCs; thus, it is important to explore their contingent effects.

In addition, physicians' knowledge sharing behavior has been investigated from the perspective of charge or free of charge (Yang and Ju, 2016; Guo et al., 2017), but insufficient attention has been paid to patients' involvement in stimulating physicians' online knowledge sharing (Meng et al., 2021). The primary participants in an OHC platform (patients) play a crucial role in value co-creation between physicians and patients (Van Oerle et al., 2016). Attracting patients to participate in an OHC platform will better promote physicians' online knowledge sharing behavior and increase the operational effectiveness of the OHC platform. The stimulus–response framework, as an important psychological model, reveals the effect of environmental factors on human's behavior (Reichl et al., 2006; Li and Chang, 2012; Giesen et al., 2020). Applying the stimulus–response framework in online knowledge sharing facilitates to reveal the mechanism that physicians to learn about and interact with the patients is to receive a stimulus and respond to it accordingly and in real-time by sharing knowledge on the OHC platform. However, in the context of OHCs, few studies have investigated how stimulates from patients (patients' visit, patients' consultation) influence the response of physicians (online knowledge sharing). To address this gap, this study uses the stimulus–response framework to explore the effects of patients' visit and patients' online consultations (S) on physicians' online knowledge sharing (R) and considers the contingent roles of physicians' online expertise and online knowledge sharing experience.

Patients' Visit and Online Knowledge Sharing

Patients' visit refers to the number of patients visit the physician's homepage on the online health platform (Li et al., 2012). Online knowledge sharing refers to physicians providing free health and medical information on platforms that are available for viewers (Yan et al., 2016). Patients' visit can have a positive effect on physicians' online knowledge sharing for several reasons.

First, on the online health platform, the number of physicians' homepage views indicates their service quality (Yang et al., 2015b). Physicians with more visits may have better service quality and will be welcomed by patients (Yang et al., 2015b). Physicians are motivated by what patients like, and they are motivated to interact with patients on the online health platform, which tends to induce their knowledge sharing on the platform (Zhang et al., 2019b). Second, patients' visit has a positive effect on physicians' online reputation (Cropanzano and Mitchell, 2005). The more visits, the better the physician's online reputation, and online reputation plays a positive role in promoting knowledge sharing (Liu et al., 2016; Yan et al., 2016). Therefore, the more visits, the more knowledge sharing will be conducted by the physician. Finally, frequent patients' visit to physicians' homepages shows that patients are seeking medical knowledge and help from the articles shared by physicians. An increase in visits leads physicians to gradually understand the needs of patients. Therefore, to help their patients and serve their society (Luo et al., 2018), physicians share relevant medical knowledge on online health platforms. Based on the above argument, we propose the following hypothesis:

> ***H1:*** Patients' visit *is positively related to physicians' online knowledge sharing.*

Patients' Consultation and Online Knowledge Sharing

Patients' consultation refers to a type of consultation in which physicians and patients are at different locations via an online health platform (Wu and Lu, 2017; Atanasova et al., 2018). In the context of online health platforms, the number of consultation is an important indicator that reflects physicians' activity on the online health platform. Therefore, patients' consultation can be an important factor affecting the online knowledge sharing of physicians.

On an online health platform, patients consult physicians when they encounter health problems (Guo et al., 2017). The more patients ask physicians about health problems, the easier it is for physicians to find common problems from the questions raised by patients (Ha and Longnecker, 2010). To save time, physicians can summarize the common questions they encounter and publish the answers on the online health platform. They can then use this knowledge to improve their professional knowledge capability, which increases the possibility of publishing relevant articles on the online health platform (Zhang et al., 2019a; Meng et al., 2021). In addition, a higher number of patient consultations show that physicians are interacting with patients on the platform more; that is, physicians are more involved in the platform. The more physicians participate, the more they share knowledge (Chang and Chuang, 2011; Liu and Jansen, 2017). Based on the above arguments, we propose the following hypothesis:

> ***H2:*** *Patients' consultation is positively related to physicians' online knowledge sharing.*

The Moderating Effect of Online Expertise

Physicians' online expertise refers to the online time and experience of physicians in using online platforms (Dodel and Mesch, 2018). Physicians' high online expertise is accompanied by high levels of physicians' assets, online time, and reputation (Kessler et al., 2015), which may moderate the effects of patients' visit and patients' consultation on physicians' online knowledge sharing.

To a certain extent, online expertise reflects the physician's assets, online time, and professional skills (Kessler et al., 2015; Dodel and Mesch, 2018). Physicians with stronger online expertise have longer online time and stronger professional skills. These physicians are accustomed to the operation of the platform, have less freshness and interest in the platform, and no longer pay attention to the number of visits and consultations (Batson et al., 2002). As a result of the reduced attention to the number of visits and consultations, the relationship between knowledge sharing and the number of visits and consultations is gradually weakened. In addition, physicians with a high level of online expertise have a high online reputation and old qualifications on the platform (Van Deursen et al., 2011). These physicians publish articles on the platform and share knowledge for incentive reasons instead of paying attention to the number of visits and consultations (Meng et al., 2021). For example, a senior physician of medicine said, "if knowledge sharing can save lives, it will be worth it in my life." In this situation, the positive effect of visits and consultations of patients on physicians' knowledge sharing will be weakened. Based on the above arguments, we propose the following hypotheses:

> ***H3:*** *Online expertise weakens the positive relationship between patients' visit and physicians' online knowledge sharing.*
>
> ***H4:*** *Online expertise weakens the positive relationship between patients' consultation and physicians' online knowledge sharing.*

The Moderating Effect of Online Knowledge Sharing Experience

Online knowledge sharing experience refers to physicians' past experience in contributing knowledge to the OHC (e.g., free and publicly available health articles shared by physicians (Yan et al., 2016). Online knowledge sharing experience reflects the situation of non-monetary benefits and physicians' regular use of the platform (Zhang et al., 2017b), which may moderate the effect of patients' visit and patients' consultation on physicians' online knowledge sharing.

OHCs aim to share and address health problems and provide support and encouragement to patients (Li et al., 2012; Guo et al., 2017). Physicians with extensive knowledge sharing experience participate in online knowledge sharing for non-monetary rather than monetary benefits (Zhang et al., 2017b). This is different from some online communities (e.g., online shopping platform), where people benefit by gaining monetary rewards (Papadopoulos et al., 2013; Park et al., 2014). Physicians with extensive knowledge sharing experience share knowledge for altruistic reasons. In this context, some extrinsic factors (e.g., patients' visit and patients' consultation) may not be the main drivers of knowledge sharing in OHCs (Chung, 2014), which weakens the positive relationships between patients' visit, patients' consultation, and physicians' knowledge sharing.

Further, as a result of repetitive operation, previous knowledge sharing experiences may form a habit (Chiu et al., 2012). Habit, as an unconscious process, can influence the effects of conscious processes on decision outcomes (Chiu and Huang, 2015). So, knowledge sharing as an unconscious factor can shape a conscious decision-making process. Individuals with strong behavioral habits rely more on their past behavior rather than their cognitive evaluation, and vice versa (Honkanen et al., 2005; Chiu et al., 2012). According to Ouellette and Wood (1998), once a behavior becomes a habit, it is performed automatically and quickly, without attention. When knowledge sharing becomes a habit, physicians regularly share knowledge on the platform and do not rely on the patients' visit and patients' consultation for knowledge sharing. In this situation, online knowledge sharing experience will weaken the positive effect of patients' visit and patients' consultation on physicians' online knowledge sharing. Based on the above arguments, we propose the following hypotheses:

H5: *Online knowledge sharing experience weakens the positive relationship between patients' visit and physicians' online knowledge sharing.*

H6: *Online knowledge sharing experience weakens the positive relationship between patients' consultation and physicians' online knowledge sharing.*

In summary, the research model is presented in **Figure 1**.

METHODOLOGY

Data Connection

To avoid the self-reporting bias of surveys, this study applies objective data to test the hypotheses outlined above (Straub et al., 1995). The objective data were collected from *haodf.com* ("online good physicians" in English), a leading online health platform in China. This platform gathers more than 200,000 physicians from different hospitals throughout China and serves more than 58,000,000 patients online (Meng et al., 2021). The platform offers an ideal setting to explore physicians' online knowledge sharing for the following reasons. First, it attracts many patients' visit and consultations, which can induce physicians to share knowledge on the platform. Second, it enables physicians to share knowledge both publicly (without compensation) and privately (with compensation). Third, given the large number of participants, abundant data are generated about physicians' websites and physician–patient interactions. We developed a Java-based web crawler to collect data from *haodf.com*. The article publications and website data statistics of 66,563 physicians over 6 months (February 2017 to July 2017) were collected. After removing some samples with incomplete data, we obtained 19,032 physicians for a total number of 45,449 physician–month observations.

Measures

Dependent Variables

Online knowledge sharing (OKS) reflects physicians providing free health and medical information on platforms that are available for viewers (Yan et al., 2016). Based on previous studies (Kuang et al., 2019; Meng et al., 2021), online knowledge sharing was measured by the new number of shared free health articles in every month.

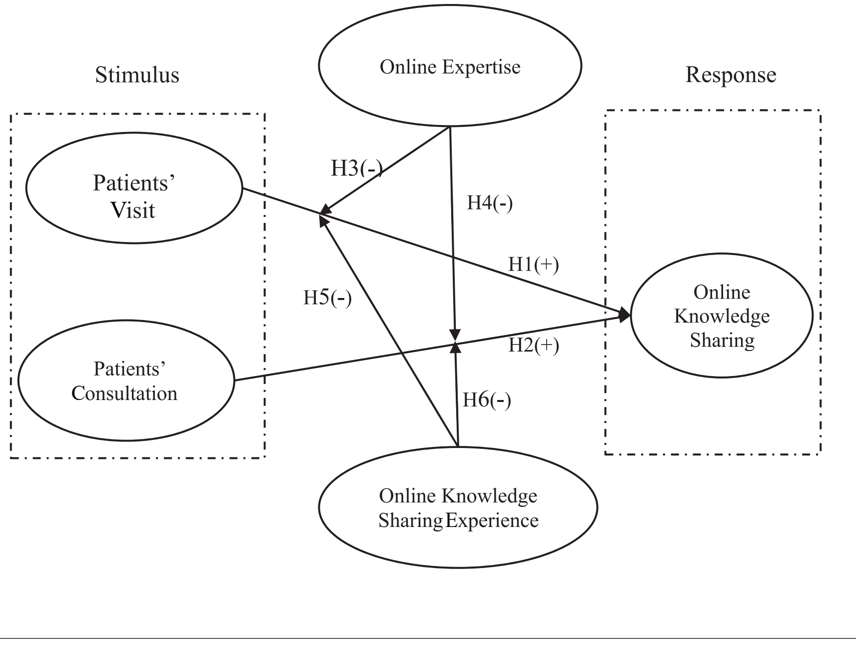

FIGURE 1 | Research model.

Independent Variables

Patients' visit (PV) reflects the number of patients who visit the homepage of a physician on the health platform. We measured patients' visit by the number of patients visiting a physician's homepage. Patients' consultation (PC) refers to a type of consultation in which physicians and patients are at different locations via online health platform (Wu and Lu, 2017; Atanasova et al., 2018). We measured patients' consultation by the number of patients' consultations on the health platform. Online expertise (OE) refers to online time and experience of physicians in using online platforms (Dodel and Mesch, 2018). We measured online expertise by the online time of the physician on the platform. Online knowledge sharing experience (OKSE) refers to physicians' past experience in contributing knowledge to the OHCs. Following the suggestion of Meng et al. (2021), online knowledge sharing experience was measured by the number of free and publicly available health articles shared by physicians previously.

Control Variables

To ensure the model had a high level of precision, based on previous studies (Zhang et al., 2019b; Meng et al., 2021), this paper included control variables as follows. *Seniority* was measured by the professional title of the physician. *Gift* was measured by the number of online gifts from patients. *Thank-you* was measured by the number of online thank you letters from patients. *Vote* was measured by the number of votes received by the physician.

Given the magnitude of the variables, following the suggestion of Kafouros et al. (2015), we took the logarithm of all variables except seniority as our final measurement. **Table 1** presents a summary of the variables.

Data Analysis

To better understand the relationship between patients' visit (PV), patients' consultation (PC), online expertise (OE), online knowledge sharing experience (OKSE), and online knowledge sharing (OKS), we applied a moderated-model analysis. In line with previous studies (Wan and Sanders, 2017; Zhang et al., 2019b), a three-model system to analyze the relationships among the variables was presented as follows:

$$\begin{aligned}
\mathrm{OKS}_{it} &= \alpha_0 + \alpha_1 Seniority_{it} + \alpha_2 Gift_{it} + \alpha_3 Thank-you_{it} \\
&\quad + \alpha_4 Vote_{it} + \alpha_5 PV_{it} + \alpha_6 \mathrm{PC}_{it} + \mu_{it} \\
\mathrm{OKS}_{it} &= \beta_0 + \beta_1 Seniority_{it} + \beta_2 Gift_{it} + \beta_3 Thank-you_{it} \\
&\quad + \beta_4 Vote_{it} + \beta_5 PV_{it} + \beta_6 \mathrm{PC}_{it} + \beta_7 \mathrm{OE}_{it} + \beta_8 PV_{it} \\
&\quad \times \mathrm{OE}_{it} + \beta_9 PC_{it} \times \mathrm{OE}_{it} + \varepsilon_{it} \\
\mathrm{OKS}_{it} &= \gamma_0 + \gamma_1 Seniority_{it} + \gamma_2 Gift_{it} + \gamma_3 Thank-you_{it} \\
&\quad + \gamma_4 Vote_{it} + \gamma_5 PV_{it} + \gamma_6 \mathrm{PC}_{it} + \gamma_7 \mathrm{OKSE}_{it} \\
&\quad + \gamma_8 PV_{it} \times \mathrm{OKSE}_{it} + \gamma_9 PC_{it} \times \mathrm{OKSE}_{it} + \varphi_{it}
\end{aligned}$$

Where $\mathrm{i} = 1, 2, 3, \cdots, \mathrm{N}$ indicate the numbers of observations; α_0 to α_6, β_0 to β_{10}, γ_0 to γ_{11} are the parameters to be estimated in the three equations; and μ_{it}, ε_{it}, φ_{it} are the error terms in the three equations.

Previous studies have noted that the ordinary least squares regression model is inefficient and is accompanied by estimated bias if the testing excludes time effects (Lee et al., 2014). Following the method for panel data applied by Samila and Sorenson (2010) and Lee et al. (2014), this paper applied the fixed-effects model to investigate the relationship between the explaining variables and the explained variables.

RESULTS

Table 2 presents the correlation matrix for the study measures. Since our study involved moderating effects, following existing recommendations and recent empirical studies (Cohen et al., 2003; Fischer et al., 2019; Meng et al., 2021), we applied hierarchical regression to test the hypotheses. In line with the conclusions of Brambor et al. (2006) and Hayes and Matthes (2009), centering would not offer any new or more accurate information, and would help us to overcome any problem with multicollinearity; thus, we did not mean center predictor variables. The tests of the hypotheses are presented in **Table 3**.

In Model 1, we regressed online knowledge sharing on patients' visit and patients' consultation. The results indicated that patients' visit ($b = 0.015$, $p < 0.001$) and patients' consultation ($b = 0.056$, $p < 0.001$) were positive and significantly related to online knowledge sharing. Thus, H1 and H2 are supported. For the control variables, the effects of seniority ($b = -0.008$, $p < 0.050$) and vote ($b = -0.039$, $p < 0.001$) were negative and significant, while the effects of gift ($b = 0.047$, $p < 0.001$) and thank-you ($b = 0.020$, $p < 0.010$) were positive and significant.

In Model 2, to test the moderating effects of online expertise, we computed the interaction terms between patients' visit (PV), patients' consultation (PC), and online expertise (OE), and then entered them into the regression equation after the control variables and the direct effects. The results showed that the coefficient of the interaction term (PV × OE) was negative and significant ($b = -0.006$, $p < 0.050$). Following the suggestion of Meyer et al. (2017), we calculated and plotted the marginal effect of patients' visit on online knowledge sharing at different levels of online expertise (**Figure 2**). The results indicated that as the values of online expertise increased from 1.792 to 8.030, the slope of the relationship between patients' visit and online knowledge sharing becomes flatter. It suggest that online expertise weakens the positive effect of patients' visit on online knowledge sharing. Thus, H3 is supported. The relationship between the interaction term (PC × OE) and online knowledge sharing was not statistically significant ($b = -0.0005$, $p > 0.050$). Thus, H4 is not supported.

In Model 3, to test the moderating effects of online knowledge sharing experience, we computed the interaction terms between patients' visit (PV), patients' consultation (PC), and online knowledge sharing experience (OKSE), and then entered them into the regression equation after the control variables and the direct effects. In Model 3, the relationship between the interaction term (PV × OKSE) and online knowledge sharing

TABLE 1 | Variable description.

Variables		Description	Mean	*SD*	Min	Max
Dependent variables	Online knowledge sharing	New number of shared free health articles	0.226	0.645	0	7.169
Independent variables	Patients' visit	Number of patients visiting a physician's homepage	10.048	2.087	2.398	17.859
	Patients' consultation	Number of patients' consultations on the health platform	2.885	2.499	0	10.667
	Online expertise	Opening time of physician the platform	6.789	1.067	1.792	8.030
	Online knowledge sharing experience	Number free and publicly available health articles shared by physicians previous	0.890	1.250	0	7.551
Control variables	Seniority	Professional title of the physician	2.804	0.970	1	4
	Gift	Number of Online gifts from patients	1.016	1.429	0	7.920
	Thank-you	Number of online thank-you letters from patients	0.759	1.037	0	6.066
	Vote	Number of votes received by the physician	1.612	1.312	0	6.911

TABLE 2 | Correlation matrix.

Variables	1	2	3	4	5	6	7	8	9
1.Online knowledge sharing	1.000								
2.Patients' visit	0.260	1.000							
3.Patients' consultation	0.301	0.823	1.000						
4.Online expertise	0.505	0.652	0.642	1.000					
5.Online knowledge sharing experience	0.070	0.712	0.282	0.286	1.000				
6.Seniority	0.038	0.350	0.175	0.160	0.357	1.000			
7.Gift	0.279	0.693	0.814	0.569	0.229	0.178	1.000		
8.Thank-you	0.217	0.627	0.682	0.462	0.260	0.288	0.768	1.000	
9.Vote	0.202	0.689	0.689	0.446	0.363	0.411	0.727	0.878	1.000

were statistically significant ($b = -0.062$, $p < 0.001$). We plotted the marginal effect of patients' visit on online knowledge sharing at different levels of online knowledge sharing experience (**Figure 3**). The results show that as the values of online knowledge sharing experience increase from 0 to 7.551, the slope of the relationship between patients' visit and online knowledge sharing becomes flatter. In other words, online knowledge sharing experience reduces the positive effect of patients' visit on online knowledge sharing. Thus, H5 is supported. The coefficients of the interaction term (PC × OKSE) were statistically positive and significant ($b = 0.046$, $p < 0.001$). We plotted the marginal effect of patients' consultation on online knowledge sharing at different levels of online knowledge sharing experience (**Figure 4**). **Figure 4** demonstrates that as the values of online knowledge sharing experience increased from 0 to 7.551, the slope of the relationship between patients' consultation and online knowledge sharing becomes steeper. It means that online knowledge sharing experience enhances the positive effect of patients' consultation on online knowledge sharing. These results are contrary to our hypothesis. Thus, H6 is not supported.

To check the robustness of our results, following the suggestion of previous studies (Wiener and Lee, 2020; Chin et al., 2021), we conducted supplementary analysis with random effects models to test our hypotheses. The results are presented in **Table 4**. Model 4 indicated that patients' visit ($b = 0.015$, $p < 0.001$) and patients' consultation ($b = 0.056$, $p < 0.001$) were positively and significantly related to online knowledge sharing. Thus, H1 and H2 are supported. Model 5 showed that the coefficient of the interaction term (PV × OE) was negative and significant ($b = -0.007$, $p < 0.010$), while the coefficient of the interaction term (PC × OE) was insignificant ($b = -0.0004$, $p > 0.050$). Therefore, H3 is supported but H4 is not supported. Model 6 indicated that the interaction term (PV × OKSE) was negatively and significantly related to online knowledge sharing ($b = -0.062$, $p < 0.010$), while the interaction term (PC × OKSE) was positively and significantly related to online knowledge sharing ($b = 0.046$, $p < 0.010$). Thus, H5 is supported but H6 is not supported. In summary, the results of random effects are consistent with those of fixed effects, and our results are robust.

DISCUSSION AND CONCLUSION

Discussion

During the COVID-19 pandemic, online health platforms and physicians' online knowledge sharing has played an important role in public health crisis management and disease prevention (Zhang et al., 2021). This study, based on the stimulus–response framework in psychology, investigated the reasons for, and processes of, physicians' online knowledge sharing and resulted in four significant key findings.

First, this study found support for the stimulus–response hypothesis. Patients' visit and online consultations are positively related to physicians' online knowledge sharing. This means that patients are able to stimulate physicians' online knowledge sharing (e.g., publishing online health articles). The number of patients' visit is an important indicator evaluating the online reputation of physicians (Meng et al., 2021), which is

TABLE 3 | Results of hierarchical regression.

DV: Online knowledge sharing	**Model 1**	**Model 2**	**Model 3**
	Coefficient (Standard error)	**Coefficient (Standard error)**	**Coefficient (Standard error)**
Patients' visit (PV)	0.015*** (0.003)	0.118*** (0.018)	−0.014*** (0.003)
Patients' consultation (PC)	0.056*** (0.003)	0.028* (0.014)	−0.010*** (0.003)
Online expertise (OE)		−0.033 (0.018)	
Online knowledge sharing experience (OKSE)			0.801*** (0.016)
VP × OE		−0.006* (0.002)	
CP × OE		−0.0005 (0.002)	
VP × OKSE			−0.062*** (0.002)
CP × OKSE			0.046*** (0.002)
Seniority	−0.008* (0.003)	−0.007 (0.003)	−0.004 (0.003)
Gift	0.046*** (0.004)	0.041*** (0.004)	−0.001 (0.004)
Thank-you	0.021*** (0.006)	0.020** (0.006)	0.008 (0.006)
Vote	−0.040*** (0.005)	−0.040*** (0.005)	−0.002 (0.005)
Constant	−0.057** (0.021)	−0.386** (0.122)	0.136*** (0.023)
R square	0.098	0.102	0.284

**$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (2-tailed test).*

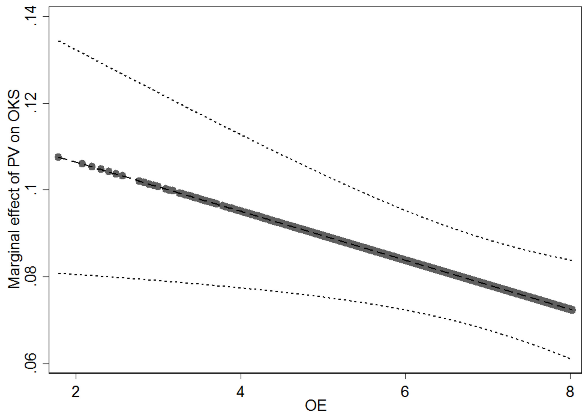

FIGURE 2 | Moderating effect of online expertise (OE) on the relationship between patients' visit (PV) and online knowledge sharing (OKS).

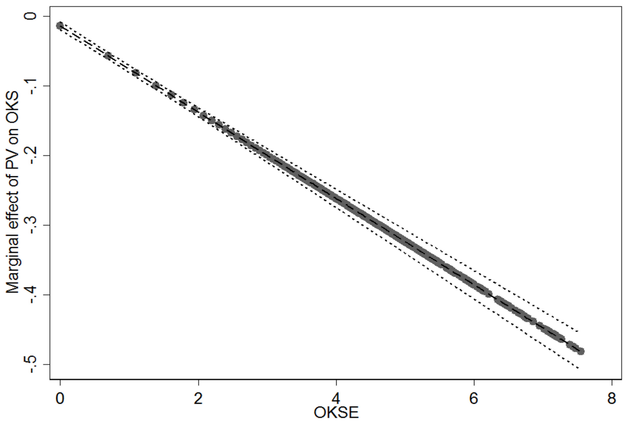

FIGURE 3 | Moderating effect of online knowledge sharing experience (OKSE) on the relationship between patients' visit (PV) and online knowledge sharing (OKS).

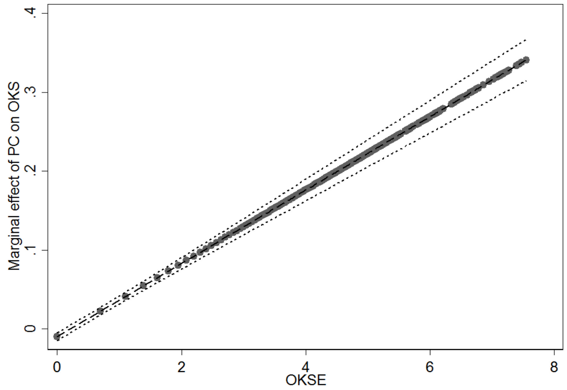

FIGURE 4 | Moderating effect of online knowledge sharing experience (OKSE) on the relationship between patients' consultation (PC) and online knowledge sharing (OKS).

a vital factor affecting their knowledge sharing behavior (Yan et al., 2016; Zhang et al., 2017b; Park and Gabbard, 2018). Patients' consultation reflects interactions between physicians and patients, and physicians actively participate in the process; the more physicians participate, the more they share knowledge (Chang and Chuang, 2011; Liu and Jansen, 2017).

Second, this study verified the moderating effect of online expertise. Physicians' online expertise reflects their online skills and experience in using online platforms (Dodel and Mesch, 2018). Physicians with a high level of online expertise feel less freshness and interest in the platform (Batson et al., 2002); in this context, they no longer pay attention to the patients' visit in online knowledge sharing. In this vein, online expertise weakens the positive relationship between patients' visit and online knowledge sharing. However, the hypothesis that online expertise alleviates the effect of patients' consultation on physicians' online knowledge sharing is not supported. One possible explanation is that patients' consultation involves frequent interactions between physicians and patients, and physicians need to focus on it (Yang et al., 2015a; Liu S. et al., 2020). Regardless of the level of online expertise, all physicians tend to attach importance to patient consultations;

TABLE 4 | Results of robust test.

DV: Online knowledge sharing	Model 1	Model 2	Model 3
	Coefficient (Standard error)	Coefficient (Standard error)	Coefficient (Standard error)
Patients' visit (PV)	0.015*** (0.003)	0.126*** (0.018)	−0.013*** (0.003)
Patients' consultation (PC)	0.056*** (0.003)	0.023 (0.014)	−0.010*** (0.003)
Online expertise (OE)		−0.018 (0.018)	
Online knowledge sharing experience (OKSE)			0.806*** (0.016)
VP × OE		−0.007* (0.002)	
CP × OE		−0.0004 (0.002)	
VP × OKSE			−0.062*** (0.002)
CP × OKSE			0.046*** (0.002)
Seniority	−0.008* (0.003)	−0.006 (0.003)	−0.004 (0.003)
Gift	0.047*** (0.004)	0.043*** (0.004)	−0.0001 (0.004)
Thank-you	0.020** (0.006)	0.020** (0.006)	0.007 (0.006)
Vote	−0.039*** (0.005)	−0.039*** (0.005)	−0.0004 (0.005)
Constant	−0.066** (0.021)	−0.471** (0.122)	0.125*** (0.023)
R square	0.098	0.102	0.283

*p < 0.05, **p < 0.01, ***p < 0.001 (2-tailed test).

thus, the relationship between patient consultations and physicians' online knowledge sharing is almost not affected by online expertise.

Finally, the moderating effect of online knowledge sharing experience was also confirmed. This study finds that online knowledge sharing experience weakens the positive relationship between patients' visit and physicians' online knowledge sharing, and enhances the positive relationship between patients' consultation and physicians' online knowledge sharing. Physicians with online knowledge sharing experience tend to form the habit of online knowledge sharing behavior and ignore the stimulus effect of patients' visit. It is indicates an individual unconscious process reducing the influence of the conscious process, consistent with prior literature (Chiu and Huang, 2015; Zhang et al., 2017a). However, online knowledge sharing expertise heightens the stimulus effect of patients' online consultation. One possible explanation is that physicians with online knowledge sharing experience discover common knowledge via patients' consultation (Li et al., 2019). In this context, patients' consultation enables physicians to summarize the common knowledge and share it online, thereby enhancing the positive relationship between patients' consultation and physicians' online knowledge sharing.

Theoretical Contributions

This study makes several theoretical contributions to the literature. First, this study extends the stimulus–response literature of psychology by introducing the stimulus–response framework to track the mechanism of physicians' online knowledge sharing. The stimulus–response framework offers a visualized framework to help researchers study the reasons for, and processes of, physicians' online knowledge sharing behavior in OHCs. In the context of OHCs, patients' visit and online consultations both have stimulating effects on physicians' online behavior response. Although much of the research based on the stimulus–response framework has been conducted to study online user behavior (Reichl et al., 2006; Xu et al., 2017; Chen and Li, 2020), to our knowledge, the framework has not been applied to investigate physicians' online knowledge sharing behavior in the context of OHCs. Thus, this study extends the stimulus–response framework literature by introducing the framework to investigate physicians' online knowledge sharing mechanism.

Second, this study extends online knowledge sharing literature by revealing the stimulus mechanism of patients' behaviors on physicians' behaviors. The primary participants in an OHC platform (patients) play a crucial role in value co-creation between physicians and patients (Van Oerle et al., 2016). Attracting patients to participate in the OHC platform will better promote physicians' online knowledge sharing behavior and increase the operational effectiveness of the OHC platform. Although physicians' online knowledge sharing behavior has been widely explored, existing literature mainly focuses on the perspective of charge or free of charge (Yang and Ju, 2016; Guo et al., 2017). Few studies have explored how patients' behavior stimulates physicians' behavior from the perspective of patients (Meng et al., 2021). Our results reveal that both patients' visit and patients' consultation are positively related to physicians' online knowledge sharing, which provides a new perspective for exploring how patients' behaviors influence physicians' behaviors on online medical platforms.

Third, this study enriches the online expertise and online knowledge sharing literature by uncovering the contingent effect of online expertise in the process of physicians' online knowledge sharing. The expertise of physicians is an important contingent factor in exploring their online behavior, but little attention has been paid to their online expertise (Guo et al., 2017; Luo et al., 2018). Our study finds that online expertise negatively moderates the effect of patients' visit on physicians' online knowledge sharing. Physicians with high online expertise tend to neglect stimulus from patients' visit because of their interests (Dodel and Mesch, 2018); thus, the positive relationship between patients' visit and physicians' online knowledge sharing is weakened. Therefore, our discoveries enrich the studies of online expertise and online knowledge sharing.

Finally, this study enriches online knowledge sharing literature by uncovering the contingent effect of online knowledge sharing experience in the process of physicians' online knowledge sharing. Physicians with high levels of online knowledge sharing experience are likely to form habits. This reduced the stimulus effect of patients' visit, which indicates an individual unconscious process reducing the influence of the conscious process, consistent with prior studies (Chiu and Huang, 2015; Zhang et al., 2017a). Online knowledge sharing experience helps physicians discover common knowledge via patients' consultation (Li et al., 2019). In this context, patients' consultation facilitates physicians to summarize the common knowledge and share it online. Thus, we find that online knowledge sharing experience strengthens the positive relationship between patients' consultation and physicians' online knowledge sharing. Hence, our study enriches the literature of online knowledge sharing by uncovering the different moderating effects of online knowledge sharing experience.

Practical Contributions

This study has several practical implications for OHC practitioners and platform managers. First, our results show that physicians' online knowledge sharing is positively promoted by patients' visit and online consultations. Patients can benefit from physicians' online knowledge sharing—for example, by obtaining free health articles, increasing their visits to OHCs (Meng et al., 2021), and then gaining social (Johnston et al., 2013) and emotional support (Yan and Tan, 2014). As a result, patients should stimulate physicians to share knowledge with the aid of more visits to physicians' homepages and more online consultations, thereby achieving value co-creation.

Second, physicians should understand their decision-making processes in terms of knowledge sharing. This study finds that physicians' online expertise and knowledge sharing experience play significant moderating roles in their online knowledge sharing. Hence, as important participants in OHCs, different groups of physicians should be aware of how their levels of online experience affect their sharing decision-making to make better decisions. For example, physicians with a low level of online expertise feel more freshness and interest in the platform, they often pay more attention to the patients' visit in online knowledge sharing. These physicians should exert their subjective initiative and actively publish free articles for attracting more patients to visit their homepages, which stimulating more online knowledge sharing in turn and creating a virtuous circle.

Finally, platform managers can use diverse strategies to stimulate different physician groups. Our results show that the stimulus effect of patients' visit is weakened by physicians' online knowledge sharing experience and online expertise. Thus, managers can introduce measures to guide more patients to browse the homepages of physicians with low knowledge sharing experience and online expertise, thereby stimulating them to share knowledge online. For example, the platform can push physicians with low level of online expertise or few published articles to patients, by launching preferential activities such as browsing and punching in, to increase the visits of physicians' homepages. Meanwhile, the stimulus effect of patients' consultation is strengthened by physicians' online knowledge sharing experience. Therefore, managers can take measures to guide patients to consult physicians with rich experience of online knowledge sharing for stimulating physicians to share knowledge. For example, the platform can recommend physicians who have published many articles to patients in need of consultation. Moreover, managers should emphasize the potential benefits (e.g., social and economic returns) of online knowledge sharing to encourage physicians to contribute persistently to OHCs (e.g., by publishing online health articles).

Limitations and Future Research

Although this study has produced interesting findings and contributed to both theory and practice, it has several limitations. First, the results of the study are based on data in the Chinese context, which may limit the generalization to other countries (Wu et al., 2019; Zhao et al., 2020; Meng et al., 2021). Future research should use data from diverse countries to verify the validity of our results. Second, this study only used online expertise and online knowledge sharing experience as moderators; however, other factors could be used in the study of physicians' online knowledge sharing, such as physicians' offline seniority and information uncertainty (Zhang et al., 2019b; Liu Y. et al., 2020). Finally, the research model in this study does not contain mediators. In fact, physicians' affective states (e.g., empathy and pleasure) caused by stimulus (Kim and Johnson, 2016; Luo et al., 2021) may affect their response in online knowledge sharing. Future research could introduce physicians' affective states as mediators to investigate physicians' online knowledge sharing.

CONCLUSION

The COVID-19 not only causes significant challenges for health systems and economic recession, but also influence physicians' online knowledge sharing. This study investigates physicians' online knowledge sharing by applying the framework of stimulus–response in psychology and considers the contingency effect of physicians' online expertise and online knowledge sharing experience. Based on the 6-month panel data of 45,449 physician–month observations from an online health platform in China, this study uncovers that patients' visit and patients' consultation benefit physicians' online knowledge sharing. Meanwhile, online expertise and online knowledge sharing experience impede the positive relationship between patients' visit and physicians' online knowledge sharing, while online knowledge sharing experience enhances the positive relationship between patients' consultation and physicians' online knowledge sharing. Our study also has theoretical contributions to the literature of stimulus–response and online knowledge sharing, and practical implications to OHC practitioners and platform managers.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

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Understanding the Effects of Emergency Experience on Online First-Aid Learning Intention: The Mediating Role of Psychological Distances and Prosociality

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The fast-paced lifestyle resulting from China's rapid economic development has caused more than 500 million sudden cardiac deaths in 2020. Online first-aid education for the public is considered a key potential solution to avoid such incidents and would have great practical value. This study focuses on understanding the impact of past first-aid experience on the intention for online learning of first-aid knowledge and skills from the perspective of individual psychological factors based on the construction level and prosociality theories. More specifically, it tests the mediating roles of psychological distances and prosociality, which reflect psychological status, in the relationship between experience and learning intention along with a series of associated demographic variables. Primary data collected *via* a survey are analyzed through regression analysis. The results show that first-aid experience has a significant positive impact on online first-aid learning intention. In addition, psychological distances from first-aid events, and prosociality, play mediating roles in the relationship between first-aid experience and learning intention. Thus, this study contributes to understanding first-aid learning intention by revealing the impact of the individual factors of psychological distances and prosociality.

Keywords: learning intention, emergency experience, psychological distances, prosociality, first-aid

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INTRODUCTION

With the rapid development of the social economy, the incidence of sudden diseases is relatively high owing to the fast pace of life and unhealthy lifestyles. Implementing correct and simple emergency rescue immediately after an emergency incidence can effectively reduce the mortality and disability rates caused by sudden diseases (Kanstad et al., 2011). Therefore, it is of great practical significance to popularize first-aid knowledge and skills and promote the population's related knowledge and skills. However, the public in China lacks opportunities to be trained formally in a standardized and systematic manner. In this regard, the online learning of first-aid knowledge and skills based on the development of online learning technology breaks through the limitations of time and space, and thus facilitates training that is more flexible, extensive, and convenient.

Past emergency experience provides an immersive experience for individuals to understand the severe consequence of emergency events. Existing conclusions deducted mixed results to understand the relationship between emergency experience and subsequent behavior. On the one hand, most people with emergency experience generally believe that such an event is unlikely to happen and pay little attention to it (Roppolo et al., 2009), leading to low intention to acquire first-aid knowledge and skills. However, other scholars believed that past emergency experience had a powerful impact on shaping the recognition and judgments about a future emergency (Weinstein, 1989; Martin et al., 2009; Demuth et al., 2016). Results of past studies suggest that past emergency experience is an essential factor to future behavior, such as people's response to the threat (Siegrist and Gutscher, 2008). Learning first-aid knowledge and skills online could help individuals better respond to emergency events in the future. This article aims to understand the relationship between emergency experience and first-aid online learning intention.

It is also important to understand how past experience has an effect on learning the knowledge and skills to deal with emergency incidents. We propose that two interpretation paths may generate the relationship between experience and learning. First, individuals have a more direct, in-depth perception when participating in, or observing, emergency events. Their cognition of first-aid events changes, and then, they may be more likely to acquire relevant knowledge to avoid corresponding risks than those who have not experienced such events (Trope and Liberman, 2010). Second, the emergency experience can trigger behaviors to help others manage current difficulties. Prosociality from watching urgent events can motivate people to learn skills for helping others (Penner et al., 2005).

LITERATURE REVIEW

It has been proved that experience could motivate learning behavior (Liu et al., 2017). Further, the experience of emergencies can increase an individual's learning intention regarding relevant knowledge and skills (Hoffmann and Muttarak, 2017). As a predictive indicator of behavior, learning intention can reflect the subjective possibility that an individual will implement a certain behavior (Ajzen and Fishbein, 1980). Learning intention is usually defined as the degree of personal willingness or a plan to be put into action to narrow the gap between oneself and the desired goal through education and training (Kyndt et al., 2011).

We suggest that emergency experience may influence online first-aid learning intention in two ways. First, the relationship between emergency experience and learning intention is affected by the psychological distances (PDs) from emergency events. PDs guide people's behavior by changing their perception of objective things (Trope et al., 2007). For example, merchants can reduce customers' PDs from online shopping by uploading pictures of physical stores, thus improving purchase intention and encouraging first-time purchases (Darke et al., 2016). Next, the relationship between emergency experience and learning intention is affected by prosociality. The surrounding environment has an impact on the prosociality of individuals. More specifically, when people observed the prosocial behaviors of others, their prosociality may increase, and they are more likely to help others in the future (Krupka and Weber, 2009).

Role of Psychological Distances

Different people's understanding of the same objective events varies because the PDs that people perceive differ (Liberman and Förster, 2009). According to the construal level theory, PDs are the degree to which an object is removed from the self, including dimensions of space distance, temporal distance, social distance, and uncertainty (Wakslak et al., 2006; Trope and Liberman, 2010). When a emergency event takes place in more remote place, occurs in the more distant future, happens to people less like oneself, and is less likely to occur, the event is more psychologically distant (Liu et al., 2017).

The literature has proved that subjective experiences are essential factors that affect PDs (Jackson, 1982; Ramachandran and Hirstein, 1997; Van Boven et al., 2010). For example, individuals' PDs could be reduced by the direct experience of climate change events, and then, PDs would increase their attention to climate change (Akerlof et al., 2013; McDonald et al., 2015). Moreover, the direct experience of driving pure electric vehicles reduces consumers' PDs from electric cars and improves their consumption intention (Skippon and Garwood, 2011).

Moreover, construal level theory holds that PDs change people's level of construction of events, which causes changes in their thoughts and behaviors (Trope et al., 2007). Individuals will use concrete, detailed, low-level words to construct events to which individuals are psychologically close. Conversely, they use abstract words to make them at a high level to represent distant events. (Liberman and Trope, 1998, 2008). For example, Spence et al. (2012) found that lower PDs made the public pay more attention to climate change and produced more avoidance behavior to mitigate the impact of climate change. In addition, the level of construction also affects psychological distances (Trope et al., 2007). For example, experiencing an emergency will make people pay attention to the low-level, detailed information of the emergency so that they will be more mentally close to the emergency.

Role of Prosociality

Prosociality is an essential feature of humans correlated with cognition, emotion, and behavior to benefit others through social interaction (Zaki and Mitchell, 2013). People with prosociality tend to be more sensitive to the pain and needs of others, show more concern for others, and are more willing to help others (Caprara et al., 2012).

Various factors can affect an individual's daily life and thus cause them to exhibit various types of prosocial behaviors (Eisenberg and Fabes, 1998). Personal experience can affect prosociality (Vollhardt and Staub, 2011). Moreover, when people observe the prosocial behaviors of others, their prosociality would increase (Rand et al., 2012). Another study showed that the charity level of staff working in the high-level charity department of a charitable organization would increase by being affected by other staff (Christakis and Fowler, 2009).

Prosociality can provide people with internal support and guide their behavior, regardless of the motivation to ask for a return (Berman et al., 2015). Batson (2014) found that when bystanders saw others in trouble, prosociality would make them feel empathy and sympathy and act to help others. Thus, prosociality will encourage the public to learn and use helpful skills to benefit others (Penner et al., 2005).

HYPOTHESES DEVELOPMENT

The present study aims to understand how the emergency experience affects online first-aid learning intention. We suggest two ways in which emergency experience may influence online first-aid learning intention. One possible explanation is that emergency experience can improve the online first-aid learning intention through changing people's PDs from first-aid events. We also suggest that the relationship between emergency experience and learning intention is affected by prosociality.

The previous study has highlighted that experience would affect future avoidance behavior (Sönmez and Graefe, 1998). An existing study has also shown that experiencing emergencies increases the public's perceptions and risk awareness about crises to improve their willingness to learn relevant risk-aversion skills (Hoffmann and Muttarak, 2017). Learning relevant risk avoidance knowledge and skills is an effective risk avoidance behavior, which can enhance people's ability to respond to similar incidents in the future and reduce the incidence of sudden death. First-aid learning, which is one of the specific behaviors to avoid risks in the future, requires further understanding and combines theory and practice. The observation of an emergency event will undoubtedly enhance the public's perception of the crisis and cognition of the event, which will improve the public's willingness to learn first aid. Therefore, we suggest that emergency experience can increase people's online first-aid learning intention. According to this argument, we propose the first hypothesis:

H1: *Emergency experience has a positive impact on online first-aid learning intention.*

Previous studies have found that experiencing a sudden disaster affects people's risk avoidance behavior by decreasing their PDs from risk (Spence et al., 2012). Therefore, we suggest that PDs mediate the effect of emergency experience on online first-aid learning intention. Experiencing an emergency means that the distance between the individual and the event is changed in the four dimensions of temporal distance, space distance, social distance, and possibility. The PDs between the public and the emergency event are reduced. Therefore, experiencing emergency events may affect individuals' PDs from emergency events. Previous studies have also shown that personal experience directly affects people's PDs from objective things (Van Boven et al., 2010).

At the same time, according to the construal level theory, changes in PDs could alter people's construal level of exact items and ultimately reflect in their thoughts and behaviors (Trope et al., 2007). For individuals, emergency experience changes the temporal distance, space distance, possibility, and social distance of emergency events which means that the emergency experience reduces the psychological distances. With the narrowing of psychological distances, individuals become more sensitive to risk events and are more willing to take corresponding measures to prevent such occurrences. Learning first-aid knowledge and skills is one of the specific behaviors for preventive measures. Therefore, the PDs of individuals to first aid events affects the willingness to learn first aid knowledge and skills. Given the hypothesis that the emergency experience affects PDs, and that PDs affect learning intention, it is reasonable to suppose that PDs play a mediating role in the relationship between the emergency experience and online first-aid learning intention, which leads to our second hypothesis:

H2: *Individual PDs mediates the relationship between their emergency experience and online first-aid learning intention.*

We also suggest that the influence of emergency experience on online first-aid learning intention can be mediated by prosociality. Prosocial behavior is voluntary, proactive, and beneficial to others (Zaki and Mitchell, 2013). Examples of such behaviors are caregiving, mutual coordination, donations, and learning to help others (Eisenberg and Miller, 1987). Previous studies have also shown that prosocial individuals are more willing to spend time and energy helping others than individualists (De Cremer and Van Lange, 2001). It is reasonable to infer that prosociality will encourage individuals to acquire some knowledge and skills helpful to others. Therefore, we believe that prosociality may affect the willingness of the public to learn first aid knowledge and skills. At the same time, prosocial tendencies will be affected by environmental factors (Hastings et al., 2007). When individuals engage in prosocial behavior in daily life or observe the prosocial behavior of others, prosociality can be strengthened (Gentile et al., 2009). To sum up, past experience of emergencies can influence prosociality to some extent. Simultaneously, prosociality can provide people with internal support and guide their behavior (Berman et al., 2015). Therefore, we test another mediation model, assuming that prosociality would mediate the relationship between emergency experience and willingness to learn first aid online:

H3: *Individuals' prosociality mediates the relationship between their emergency experience and online first-aid learning intention.*

MATERIALS AND METHODS

Research Process

In October 2020, we conducted a survey based on a well-known domestic emergency Sina Weibo account (*Jizhenyeying*) in China that emergency department physicians established in 2012. These physicians shared concise, helpful, evidence-based guidelines on emergency treatment science articles and made videos based on rich first-aid experience. This account is dedicated to promoting reliable and practical first-aid knowledge and skills. In addition, it also provides online first-aid training courses with a mixture of first-aid theories and practices. The number of followers of this account exceeded 1.9 million at the end of November 2019.

The current cross-sectional survey used online questionnaires distributed through the official emergency account. All participants voluntarily participated in the study and gave written informed consent after completing the questionnaire.

We informed them that all their answers would remain anonymous and confidential, and they could drop out at any time. The time required to answer all research questions is ∼7 mins. The design of the research protocol followed the specific ethical requirements of the authors' college.

Participants

We collected data from 804 adults using an online survey platform. We first excluded 456 samples who had studied first-aid knowledge and skills before. Subsequently, we excluded 29 samples aged above 45 years because older people are less able to learn online (Chu, 2010). Then, we used data from 319 adults. The age range of the respondents in this study was 18–44 years. They were from 98 cities of China, including all 21 megacities with a population of more than 10 million and 45 major cities across the country; 18 overseas Chinese participated from 11 different countries. The sample selection criterion was that each participant had paid attention to emergency events from online channels. The test sample demographic is shown in **Table 1**.

Research Tool

The independent variable of this study was the emergency experience, formed by the answers given to the following question: "How many emergency events have you experienced?" We measured the degree of first-aid experience of participants by the number of emergency experience they filled in.

TABLE 1 | Test sample demographic (*n* = 319).

Demographic	Category	*N*	%
Age	25 and younger	69	21.6
	25–34	159	49.8
	35–44	91	28.5
Gender	Female	76	23.8
	Male	243	76.2
Education level	Middle school and below	0	0.0
	High school	21	6.6
	College and university	238	74.6
	Master	55	17.2
	Doctor and above	5	1.6

The PDs scale consists of four PDs dimensions: temporal distance, space distance, social distance, and possibility (Spence et al., 2012). All the items were measured on a 5-point Likert scale, ranging from 1 to 5. For example, "My living area will less likely suffer emergency events (including accidents and acute diseases)." The higher the score, the nearer the PDs reported by the participants. (See **Table 2**).

The prosociality scale consists of seven items, measured using the Likert 5-point scale, with the scores ranging from 1 (strongly disagree) to 5 (strongly agree). For example, "I am pleased to help my friends/colleagues in their activities." Cronbach's alpha indicates good internal consistency (α = 0.896). The higher the score, the higher the prosociality reported by the participant. (See **Table 3**).

Last, our dependent variable is online first-aid learning intention, which consisted of answers to the following four

TABLE 3 | Likert scale of prosocial.

Questions	5	4	3	2	1
Likert scale of prosocial					
1. I am pleased to help my friends/colleagues in their activities	Strongly agree	Agree	Normal	Disagree	Strongly disagree
2. I share the things that I have with my friends	Strongly agree	Agree	Normal	Disagree	Strongly disagree
3. I try to help others	Strongly agree	Agree	Normal	Disagree	Strongly disagree
4. I am available for volunteer activities to help those who are in need	Strongly agree	Agree	Normal	Disagree	Strongly disagree
5. I am emphatic with those who are in need	Strongly agree	Agree	Normal	Disagree	Strongly disagree
6. I am willing to make my knowledge and abilities available to others	Strongly agree	Agree	Normal	Disagree	Strongly disagree
7. I try to be close to and take care of those who are in need	Strongly agree	Agree	Normal	Disagree	Strongly disagree

TABLE 2 | Likert scale of PDs.

Questions	Scale				
	5	4	3	2	1
Likert scale of PDs					
1. succnsimMy living area is likely to suffer emergency events (including accidents and acute diseases)	Strongly agree	Agree	Normal	Disagree	Strongly disagree
2. Emergency events is likely to have a big impact on me.	Strongly agree	Agree	Normal	Disagree	Strongly disagree
3. When, if at all, do you think you will suffer the emergency events?	We are already feeling the effects	One month later	Half year later	Several years later	Never
4. I am uncertain that emergency events is really happening	Strongly disagree	Disagree	Normal	Agree	Strongly agree

questions: "I intend to look for information about first-aid courses and learning activities in which I could participate"; "I intend to participate in a first-aid learning activity within the next year"; "Sometimes, I think about following a first-aid training within the next year"; "I intend to talk with persons in my surroundings about first-aid courses or pieces of training that I could follow". Participants answered on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The higher the score, the higher the participant's willingness to learn.

The demographic scale assessed the participants' age, gender, and education level. All tools were first pre-tested on a similar sample of adults ($N = 32$), and no difficulties were reported related to the items used in the questionnaire. We used SmartPLS 3 to analyze our data.

RESULTS

The mean value, standard deviation, and correlations of the main variables are shown in **Table 4**.

This study explored the mediating effects of PDs and prosociality on the relationship between emergency experience and learning intention. The total influence of emergency experience on online first-aid learning intention (without considering mediating factors) was significant [path coefficient $= 0.112$, $t = 2.523$, $p < 0.01$, SE $= 0.044$, 95% CI (0.052, 0.208)], supporting Hypothesis 1.

First, we tested the relationship between emergency experience and PDs, and the relationship between PDs and online first-aid learning intention without the mediating role of PDs. Emergency experience also had a significant effect on PDs [path coefficient $= -0.571$, $t = 10.689$, $p < 0.01$, SE $= 0.053$, 95% CI (-0.677, -0.467)]. In addition, PDs and learning intention were significantly positively correlated [path coefficient $= -0.440$, $t = 9.830$, $p < 0.01$, SE $= 0.045$, 95% CI (-0.539, -0.362)], indicating that individuals with smaller PDs are more likely to have online first-aid learning intention. In the model with the mediator of PDs, PDs was a significant predictor of online first-aid learning intention [path coefficient $= -0.255$, $t = 2.035$, $p < 0.05$, SE $= 0.125$, 95% CI (-0.478, -0.026)]. The direct effect of emergency experience on learning intention was insignificant [path coefficient $= 0.037$, $t = 1.107$, $p = 0.268$, SE $= 0.034$, 95% CI (-0.029, 0.103)]. However, the indirect effect of emergency experience on learning intention through PDs was significant, suggesting the relationship between emergency experience and learning intention is mediated by PDs, supporting Hypothesis 2. **Figure 1** shows the mediation model that contains the values of the normalized coefficients for each relationship between variables.

Similarly, we found a significant correlation between emergency experience, prosociality, and learning intention. More specifically, higher emergency experience was associated with higher prosociality levels [path coefficient $= 0.103$, $t = 2.078$, $p < 0.05$, SE $= 0.050$, 95% CI (-0.166, 0.1622)]. In addition, prosociality and online first-aid learning intention were significantly positively correlated [path coefficient $= 0.467$, $t = 9.125$, $p < 0.01$, SE $= 0.051$, 95% CI (0.359, 0.558)], indicating that individuals with higher prosociality are more willing to learn. In the model with prosociality as the mediator, prosociality

TABLE 4 | Descriptive statistics and Pearson correlation matrix.

Variable	Mean	SD	Cronbach's α	C1	C2	C3	Exp	PDs	Pro	LI
C1	2.069	0.705	–	1	–	–	–	–	–	–
C2	2.138	0.531	–	0.176	1	–	–	–	–	–
C3	1.762	0.426	–	0.086	0.159	1	–	–	–	–
Exp	0.245	0.551	–	0.029	0.035	−0.072	1	–	–	–
PDs	3.843	2.171	–	−0.070	−0.089	−0.068	−0.574	–	–	–
Pro	2.765	5.016	0.896	0.026	0.063	0.097	0.084	−0.277	0.760	–
LI	2.924	3.645	0.850	0.073	0.073	0.172	0.103	−0.237	0.450	0.830

C1, C2, and C3 refer to three control variables: age, education, gender; Exp, PDs, Pro and LI refer to emergency experience, psychological distances, prosociality, and online first-aid learning intention.

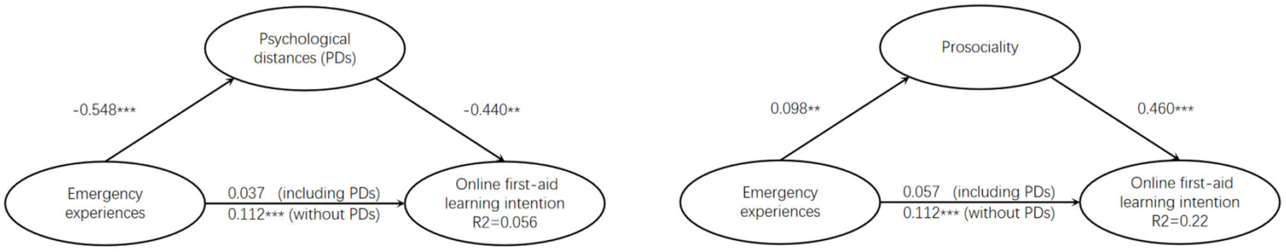

FIGURE 1 | Psychological distances (PDs) and prosociality as mediators between emergency experiences and online first-aid learning intention.

was a significant predictor of online first-aid learning intention [path coefficient = 0.460, $t = 8.776$, $p < 0.01$, SE = 0.052, 95%CI (0.361, 0.566)]. The direct effect of emergency experience on learning intention was insignificant [path coefficient = 0.057, $t = 1.541$, $p = 0.123$, SE = 0.037, 95% CI (−0.018, 0.128)]. However, the indirect effect of emergency experience on learning intention through prosociality was significant, suggesting that the relationship between emergency experience and learning intention is fully mediated by prosociality. Thus, Hypothesis 3 was supported. **Figure 1** shows the mediation model that contains the values of the normalized coefficients for each relationship between variables.

Additionally, we conducted a bootstrap analysis to estimate the mediating effect with 319 samples (Preacher et al., 2007; SPSS Process Macro Model 4). For hypothesis 2, the covariates were the same as the results showed in **Table 2**, and the results of the mediating effect was: path coefficient = 0.140, $t = 2.266$, $p = 0.024$, SE = 0.062, 95% CI (−0.067, 0.225). For hypothesis 3, the covariates were also the same with the results showed above, and the result of mediating effects was: path coefficient = 0.045, $t = 1.899$, $p = 0.058$, SE = 0.024, 95% CI (−0.003, 0.092).

At last, we performed a sensitivity analysis G∗Power 3.1 to examine the statistical power of this article (Faul et al., 2007). For hypothesis 2, the size of the smallest effect in our model requested Cohen's f 2 = 0.43. With an alpha = 0.05, power = 0.9, and sample of 319, the smallest f 2 requested 0.25. For hypothesis 3, the size of the smallest effect requested Cohen's f 2 = 0.27. With an alpha = 0.05, power = 0.9, and sample of 319, the smallest f 2 requested 0.26. All the effects were above the value of the predicted minimal detectable effect size, which suggests that this study is appropriately powered.

DISCUSSION

As expected, emergency experience and online first-aid learning intention had a significant and positive relationship. In addition, we found that PDs and prosociality played mediating roles in the relationship between emergency experience and online first-aid learning intention.

First, the results showed that emergency experience could significantly predict online first-aid learning intention. Fewer studies have directly examined this relationship. However, existing studies have shown that experiencing a disaster may increase individuals' awareness about the potential for destruction and enhance their intention of acquiring disaster-related knowledge and skills to cope with subsequent disaster threats (Sattler et al., 2000).

Second, the results suggested that emergency experience affected online first-aid learning intention through the mediating role of PDs. The findings in this study indicated that emergency experience significantly predicted PDs. In line with existing studies, perceptions of PDs could be influenced by subjective experience (Jackson, 1982), which experience may generate. Meanwhile, the findings in this study suggested that PDs are significantly associated with online first-aid learning intention. Other studies have already found that PDs may influence subsequent behaviors. For example, PDs from climate change could predict people's willingness to engage in pro-environmental conduct (Wang et al., 2019). Further, this study found a significant mediating role of PDs in the relationship between emergency experience and online first-aid learning intention.

Last, the results also showed the mediation path of prosociality between emergency experience and online first-aid learning intention. We confirmed that prosociality was positively associated with the emergency experience. Studies have found that when people observe prosocial behavior in others, their prosocial tendencies may increase (Van Baaren et al., 2004). As the literature has already indicated, prosociality can provide people with internal support and guide their behavior, such as learning behavior (Berman et al., 2015), regardless of the motivation to ask for a return. Our findings confirm that prosociality is positively associated with online first-aid learning intention. People experience emergency events and observe others' prosocial behaviors, which can strengthen prosociality and increase people's tendency to learn first-aid knowledge and skills to help others.

CONCLUSION

This study investigated how experiencing an emergency influenced online first-aid learning intention and found support for all the hypotheses.

Firstly, we found that emergency experience significantly predicted online first-aid learning intention without mediators, enriching relevant research on the influencing factors of online first-aid learning intention.

Secondly, this article verified the mediating role of PDs and prosociality in this relationship, expanding the theoretical analysis of the factors affecting online first-aid learning intention. On the one hand, based on construal level theory, the influence of emergency experience on online first-aid learning intention through PDs is explored, and the application of construal level theory is extended. The emergency experience greatly affected the psychological distances from emergency events, and the PDs of emergency events significantly influenced online first-aid learning intention. However, emergency experience had no significant direct influence on online first-aid learning intention on adding the mediator of the PDs of emergency events, illustrating the full-mediation effect of the PDs. On the other hand, the conclusions of this article also extend the application of prosocial. The results showed that emergency experience significantly affected prosociality and greatly influenced online first-aid learning intention. Meanwhile, emergency experience had no significant direct influence on online first-aid learning intention when adding the mediator, illustrating a full-mediation effect of prosociality.

Limitations and Future Research

Although this study yielded significant research findings, it has certain limitations. First, we collected data from a well-known domestic emergency account. We focused on promoting the online first-aid learning intention of individuals who were concerned about emergency care. However, people within China generally lack the knowledge and skills related to first aid and are unaware of the importance of acquiring first-aid knowledge and skills. Therefore, future research can be conducted to promote the first-aid learning intention of the general public. Second, since the online learning ability of older people is relatively weak, we focused on those <45 years old. Future research can also expand the study of online first-aid learning intention by including middle-aged and older people.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

SZ: acquisition of data, conception and design of study, analysis and interpretation of data, drafting the manuscript, and approve final paper for publication. HG: acquisition of data, conception and design of study, drafting the manuscript, and approve final paper for publication. XJ: revise the manuscript critically for important intellectual content and approve final paper for publication JM: acquisition of data and approve final paper for publication. All authors contributed to the article and approved the submitted version.

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The Impact of Health Information Privacy Concerns on Engagement and Payment Behaviors in Online Health Communities

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Online health communities (OHCs) have enjoyed increasing popularity in recent years, especially in the context of the COVID-19 pandemic. However, several concerns have been raised regarding the privacy of users' personal information in OHCs. Considering that OHCs are a type of data-sharing or data-driven platform, it is crucial to determine whether users' health information privacy concerns influence their behaviors in OHCs. Thus, by conducting a survey, this study explores the impact of users' health information privacy concerns on their engagement and payment behavior (Paid) in OHCs. The empirical results show that users' concerns about health information privacy reduce their Paid in OHCs by negatively influencing their OHC engagement. Further analysis reveals that if users have higher benefit appraisals (i.e., perceived informational and emotional support from OHCs) and lower threat appraisals (i.e., perceived severity and vulnerability of information disclosure from OHCs), the negative effect of health information privacy concerns on users' OHC engagement will decrease.

Keywords: privacy concerns, health information, online behavior, payment behavior, online health communities

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INTRODUCTION

Supported by the rapid development of cutting-edge internet technologies, online health communities (OHCs) are enjoying unprecedented popularity because of the increased demand for timely and high-quality medical services (Nangsangna and Da-Costa Vroom, 2019; Wong and Cheung, 2019; Wang X. et al., 2020). Additionally, the COVID-19 pandemic may have further fostered their use due to individuals' concerns about infection (Gong et al., 2020; Wang D. et al., 2020; Huang et al., 2021). For instance, Chunyu, one of the most popular OHCs in China, has 140 million active users and 630,000 health professionals, cumulatively serving more than 400 million patients. Moreover, OHCs provide a platform for patients to access health information, share treatment solutions, discuss medical concerns, and consult health professionals about medical issues (Yan and Tan, 2014; Zhang et al., 2018; Silver and Huang, 2020; Dahl et al., 2021). More importantly, OHCs generate enormous economic (Nambisan, 2011) and social value (Goh et al., 2016; Liu S. et al., 2020). For instance, engaging in OHCs not only provides patients with informational and social support (Mo and Coulson, 2012; Petrovčič and Petrič, 2014; Zhang et al., 2018; Agarwal et al., 2019), but also narrows the gap in the quality of medical services between urban and rural areas (Goh et al., 2016; Cao and Wang, 2018). Online health communities also allow the relationship between health professionals and patients to be improved (Liu Q. B. et al., 2020). However, some people may be reluctant to engage in OHCs due to privacy concerns, as sharing of information in OHCs is inevitably linked with the possibility of privacy violations. A survey by Auxier et al. (2020) showed that most users feel insecure about their personal information and that they have little or no control over it. In the context of health information, the consequences of data breaches are significant (Grundy et al., 2019). For instance, users may face social stigma and discrimination when buying insurance and finding jobs (Rohm and Milne, 2004; Goldfarb and Tucker, 2012; Zhang et al., 2017; Pettinico et al., 2020). Thus, this study focuses on the impact of users' health information privacy concerns on their engagement and payment behavior (Paid) in OHCs and the moderating effects of users' benefit appraisal (BA) and threat appraisals (TA) for information-sharing behaviors.

Although some scholars have analyzed the impact of health information privacy concern on information disclosure intention in OHCs (Zhang et al., 2017), the influence of privacy concerns on some forms of engagement needs to be explored. Therefore, we extend the existing literature by exploring the relationship between health information privacy concerns and users' information consumption, information production, and Paid in OHCs. The extant research has analyzed the impact of information privacy concerns on users' online engagement. As online activities play an increasingly important role in people's everyday lives, it is widely acknowledged that privacy concerns influence users' online behaviors (Dinev and Hart, 2005; Jang and Sung, 2021). Users may have a completely different attitude toward health records, financial information, personal identity, and eating habits (Smith et al., 2011; Gal-Or et al., 2018; Pettinico et al., 2020; Slepchuk et al., 2022), as well as varying sensitivities to privacy concerns (Jozani et al., 2020). When users have a more robust privacy control, they have increased awareness of how their data are collected and used, tend to have lower privacy concerns, and engage more frequently with online communities (Jozani et al., 2020), for example, by making more online payments for services. However, the privacy concerns on OHC are unique and important compared to other online platforms, which could be clarified from the much more serious consequences of privacy violation (e.g., discrimination and social stigma). For example, when people with infectious diseases (e.g., Tuberculosis, Hepatitis B) seek treatment advice on OHCs, they may face employment discrimination by the employer if their personal information is leaked. Also, lesbian, gay, bisexual, and transgender people may encounter discrimination when the sexual orientation they choose on OHC is exposed to their friends or family. Thus, considering the high sensitivity of health information (Kopalle and Lehmann, 2021), different motivations for engagement (Ward et al., 2005), and strict requirements for information accuracy (Zhao and Zhang, 2017), the influencing mechanism may show a different pattern, while conclusions based on other online communities should not be extended directly to OHCs. To this end, the relationship between users' health information privacy concerns and their OHC behaviors should be explored.

The previous research has not considered the moderating effect of users' perceived benefits and threats of sharing decision-related information on their OHC behaviors. As for the perceived benefits, people could obtain social support (e.g., informational support and social support) by participating in OHCs, where they can search for health information, receive suggestions on health issues, and obtain timely medical help in a more convenient, efficient, and effective manner (Wang X. et al., 2020), as well as reduce their stress and loneliness by talking to people in similar situations. Sharing of information is inevitably linked to privacy violations that may lead to negative consequences such as employment issues, insurance discrimination, identity theft, blackmail, targeted ad, and embarrassment (Crossler and Bélanger, 2019; Pettinico et al., 2020; Slepchuk et al., 2022), which increase users' TA of their OHC engagement. Given that previous research suggests that people may act less rationally when they weigh the benefits and threats of OHC engagement (Barth et al., 2019; Jang and Sung, 2021), it is reasonable to assume that users' evaluation of potential benefits and threats may moderate the relationship between users' health information privacy concerns and their OHC behaviors.

Thus, by conducting a survey on Credamo (a platform that provides scientific questionnaire data services for scholars in more than 1,800 universities worldwide), this study explores the impact of users' health information privacy concerns on their engagement and Paid in OHCs and the moderating effects of users' BA and TA for information-sharing behaviors. We find that users' health information privacy concerns have a negative relationship with their Paid in OHCs, which is mediated by users' OHC engagement. Additionally, users' benefit appraisals (BA) regarding informational and emotional support from OHCs positively moderate the negative relationship between their concerns about health information privacy and their OHC engagement. Further, users' TA regarding the severity and vulnerability of information sharing in OHCs negatively moderate the effect.

LITERATURE REVIEW

Health Information Privacy Concerns and Online Engagement

Users must accept service providers' privacy terms before being granted access to online platforms; these terms typically state that users agree to provide their private information as well as grant service providers the right to use their data (Bansal et al., 2010; Zhang et al., 2017). Nowadays, online platforms automatically track users' behavior and constantly collect data (Dogruel et al., 2017; Wottrich et al., 2018). They tend to share said data with third parties such as businesses and the government (Acquisti et al., 2015). Inevitably, this is associated with an increased risk of privacy violations (Crossler and Bélanger, 2019; Gerhart and Koohikamali, 2019). Thus, the lack of basic security regulations on online platforms (Pour et al., 2019) fuels privacy concerns, as users' private information may become exposed (Malm, 2018) and their anonymity could become compromised—only 15 demographic features are needed to correctly identify an individual based on online data (Rocher et al., 2019).

The extant research suggests a negative relationship between information privacy concerns and users' engagement (UE) in online communities, which can be analyzed from two perspectives: the sensitivity of the information and users' control over their data (Büchi et al., 2016; Jozani et al., 2020). Privacy concerns are affected by information sensitivity, whereas the level of sensitivity is determined by potential monetary, physical, social, and psychological risks caused by misuse (Milne et al., 2016; Gu et al., 2017; Kim et al., 2019). For instance, when information with a low sensitivity level (e.g., dietary habits) is collected, users may not be concerned; since the service provider may process the data comprehensively, more customized services will be provided and enhance users' experiences (Smith et al., 2011; Gal-Or et al., 2018). However, information such as health information, financial information, shopping history, and personal identity is considered highly sensitive. The unintended disclosure of these personal data may cause significant consequences such as employment issues, insurance discrimination, identity theft, extortion, targeted ads, and embarrassment (Goldfarb and Tucker, 2012; Crossler and Bélanger, 2019; Pettinico et al., 2020; Slepchuk et al., 2022), which may reduce the level of user engagement in online communities (Jozani et al., 2020).

Furthermore, users feel that they have higher control over their data when they have more knowledge regarding how a specific data are collected and used (Büchi et al., 2016; Jozani et al., 2020). However, users seldom know the concrete procedure of the data collection and sharing process (Zarouali et al., 2018). A vivid example of this is the Facebook–Cambridge Analytica incident (Cadwalladr and Graham-Harrison, 2018). If users believe they have a higher degree of privacy control, their privacy concerns may be reduced, leading to higher engagement in online communities (Jozani et al., 2020). Accordingly, clear privacy notifications, the use of explicit permission requests and more restrictive privacy settings, and legislative actions could reduce users' privacy concerns and motivate them to be engaged (Acquisti et al., 2015; Widjaja et al., 2019).

Privacy concerns comprise an important factor that influences UE in online communities (Dinev and Hart, 2005; Jang and Sung, 2021) as people's lives have become increasingly entwined with online services. Thus, the potential benefits of the engagement may outweigh users' privacy concerns when conducting a cost-benefit analysis, which may lead them to play an active role in online communities (Debatin et al., 2009). Furthermore, personal traits may serve as a moderator when users assess the privacy threats and engagement benefits (Aivazpour and Rao, 2020; Wirth et al., 2021).

Antecedents of Engagement in Online Health Communities

People decide to be involved in OHCs by analyzing the benefits and threats of using them. The extant research has identified the antecedents of engagement, among which informational support and emotional support are the most significant (Ray et al., 2014; Gibbs et al., 2016; Yan et al., 2016; Wang et al., 2017). Informational support and emotional support, taken together, comprises social support (Chen et al., 2020), which has been regarded as the key benefit for engagement in OHCs sought by the users (Welbourne et al., 2013; Yan and Tan, 2014; Zhang et al., 2018). First, regarding the informational support, OHCs serve as platforms that connect patients in similar situations (Chou et al., 2018; Li et al., 2018). By communicating with each other, patients may obtain timely treatment solutions more conveniently and efficiently (Wang X. et al., 2020), especially considering the significant medical burden (Wu and Lu, 2018) of Chinese hospitals, where it is quite difficult to make an appointment with elite physicians (Huang et al., 2021). Moreover, searching for an information in OHCs is cost-effective, which may increase the possibility that patients use OHCs (Gao et al., 2021), since the high costs of medical treatment may worsen patients' physical health due to stress (Gao et al., 2021). Second, emotional support is also important for patients (Yan and Tan, 2014; Gibbs et al., 2016), who require sympathy, encouragement, companionship, and other kinds of emotional support (Jin et al., 2016). The OHCs may serve as a source of emotional support by allowing users to communicate with each other (Yu et al., 2015). Compared with health professionals' suggestions—which are more direct due to doctors' tight schedules (Wang L. et al., 2020)—exchanges in OHCs are more emotionally supportive (Van Oerle et al., 2016) and can reduce patients' stress (Rains and Young, 2009; Goldsmith et al., 2013). Third, regarding additional factors, psychological benefits like individual reputation, self-esteem, and self-efficacy also facilitate people's engagement with OHCs (Van Uden-Kraan et al., 2009; Bansal et al., 2010; Mo and Coulson, 2012; Petrovčič and Petrič, 2014). Moreover, by providing suggestions and helping others, users may obtain more accurate medical knowledge and increase their health literacy, eventually developing non-professional expertise (Nettleton et al., 2005; Griffiths et al., 2012; Chen et al., 2019). The safety concerns related to the COVID-19 pandemic provide another reason for the usage of online medical services (Gong et al., 2020; Huang et al., 2021), as nearly 41% of cases are associated with hospital visits (Wang D. et al., 2020).

Certain risks may reduce the benefits from engagement in OHCs and impair people's eagerness to participate. The previous research has mainly focused on concerns regarding health misinformation. Additionally, oversimplification (Zhao et al., 2021), lack of scientific evidence (Chou et al., 2018), and deliberate distortion (Waszak et al., 2018) may generate misinformation. The lack of gatekeepers causes misinformation to spread quickly (Bode and Vraga, 2017; Li et al., 2022). Additionally, people who lack health and scientific knowledge may be misled *via* the echo chamber effect (Brady et al., 2017; Vogel, 2017). Therefore, for health issues, the accuracy of the information is important because misinformation may lead to poor health outcomes or even death (Zhao and Zhang, 2017). Thus, using OHCs carries significant risks (Chen et al., 2018). Although some cutting-edge technologies, such as deep learning and machine learning (Sicilia et al., 2018; Kumar et al., 2019; Ruokolainen and Widén, 2020; Song et al., 2021) are used to develop a filtering system for misinformation; however, these methods still face many challenges and cannot fully eliminate risks (Li et al., 2022). Thus, people should exercise caution when seeking advice through OHCs to avoid misinformation (Pluye et al., 2019).

Health professionals are significant participants in OHCs and their decision process for engagement is also worth investigating in order to have a comprehensive view of the antecedents of engagement in OHCs. Three main drivers can be identified in prior literature on engagement in OHCs (Zhou et al., 2019). First, there is technical competence, which refers to the ability to provide patients with professional services (Robin DiMatteo and Hays, 1980). Many researchers have found a positive relationship between health professionals' technical competence and OHC engagement (Zhou et al., 2018, 2019; Li et al., 2019). Online services may also improve health professionals' performance in hospitals, including operational efficiency, resource utilization efficiency, and patient satisfaction, which may, in turn, enhance their technical competence and satisfy their self-efficacy (Wu et al., 2021). Second, regarding online reputation and economic rewards, positive relationships have been identified among engagement in OHCs, online reputation, and economic rewards (Zhang et al., 2017). For health professionals, having a good reputation not only helps them improve their self-efficacy and achieve internal satisfaction (Constant et al., 1996) but also brings potential economic benefits. In the context of information asymmetry (Yan et al., 2016), wherein patients choose their physicians, they often use their online reputation as reference (Deng et al., 2019). A higher online reputation is associated with more appointments (Liu et al., 2016). In addition, more votes and thumbs will be received with an increasing number of views of their homepages (Luo et al., 2017; Deng et al., 2019; Li et al., 2019). Therefore, health professionals are motivated to provide services in OHCs, which will, in turn, gradually help them build their brand (Lu and Wu, 2016), attract more patients, and increase sales (Li et al., 2019), eventually resulting in economic and social benefits (Guo et al., 2017).

Nevertheless, two factors may prevent health professionals from participating in OHCs. First, as specialists, health professionals must ensure that their answers are accurate, professional, and precise, compared with normal users (Hennig-Schmidt and Wiesen, 2014), since even a small mistake may incur tremendous criticism that potentially damages their reputation. In other words, health professionals pay a high price when helping others in OHCs (Zhang et al., 2017). Second, health professionals in China are required to carry out scientific research outside of their working hours. Thus, resource constraints (e.g., limited time and energy) may prevent them from continuing their online activities (Wang L. et al., 2020).

Summary

After reviewing relevant literature comprehensively, to the best of our knowledge, the research gap could be concluded into the following three aspects. First, few studies have been conducted on the impact of information privacy concerns on users' OHC engagement. Second, previous research has mainly discussed UE in OHCs, whereas Paid remains relatively unexplored. Third, although many scholars have suggested that people may become less rational when carrying out benefit-threat analysis, BA and TA within the context of OHCs are not clarified.

To fill in these research gaps, this study takes health information privacy concerns into the antecedents' analysis of UE in OHCs, and sheds light on users' Paid in OHCs, while also incorporates BA and TA within the context of OHCs. All the results and conclusions are based on and summarized from a well-designed survey that is conducted on a professional scientific data services platform, Credamo.

HYPOTHESIS DEVELOPMENT

Health Information Privacy Concerns and User Engagement in Online Health Communities

Users make their engagement decisions by evaluating their potential threats and benefits. To assess the potential benefits of informational and emotional support, users must accept OHCs' privacy terms and finish the form containing their health information. Unlike other online communities (Kopalle and Lehmann, 2021), information in OHCs has two main features: higher accuracy and higher sensitivity (Markos et al., 2018). First, users cannot falsify or withhold their health information due to privacy concerns because less accurate health information could lead to wrong treatment solutions or even death (Crié and Chebat, 2013). For example, if a person is allergic to a particular drug and does not inform the doctor, the doctor uses the drug and surely the effect is counterproductive. Second, the higher sensitivity of the information contained in OHCs may lead to data breaches, causing significant problems such as discrimination and annoying advertisements. Huge commercial interests motivate privacy violations. For example, in many families with newborns, advertisements for various products and services have been accurately sent to phones and mailboxes of young parents. Employers also want to buy health private data to get real health status of job applicants. Although some regulations and laws on information use have been introduced to the public (Kopalle and Lehmann, 2021), the effects of these policies remain to be seen.

In summary, if the users are prepared to engage in OHCs, it is important to ensure the accuracy of the information they disclose. Given the potential threat of information disclosure and privacy concerns, the foreseeable benefits from engagement may be hedged. Thus, we propose Hypothesis 1 as follows:

> *Hypothesis 1* (H1): Health information privacy concerns negatively influence OHC engagement.

User Engagement and Payment Decision for Services in Online Health Communities

On sharing their experiences with others, users can establish a deep and meaningful connections, which in turn enhances trust and communication among users; thus, users eventually gain informational and emotional support *via* OHCs. Users develop a sense of engagement and belongingness when they frequently share and seek information online (Wellman and Gulia, 1999; Bateman et al., 2011). The more frequently they use OHCs, the easier it is for users to get emotionally attached to OHCs

(Mirzaei and Esmaeilzadeh, 2021). Furthermore, the users tend to feel ashamed and guilty if they simply access information and emotional support without providing the same to others (Mirzaei and Esmaeilzadeh, 2021). Only when the users strike a balance between providing and receiving support can they develop a sense of belongingness, which they subsequently become afraid of losing (Guo et al., 2016; Gao et al., 2017). Therefore, most users tend to make contributions to OHCs (Bowden et al., 2018; Liu S. et al., 2020), eventually reaching a higher level of engagement (Mirzaei and Esmaeilzadeh, 2021). Obviously, the Paid is a form of higher-level engagement. For example, you will never transfer money to strangers, and will never buy services from unknown providers due to quality concerns.

Moreover, research on other online communities has shown that users are more inclined to pay for online services in order to gain stable socializing functions and entertainment value from online communities after they have become emotionally attached to said communities (Oestreicher-Singer and Zalmanson, 2013; Brettel et al., 2015; Meng et al., 2020). Thus, we develop the following hypothesis:

> *Hypothesis 2* (H2): OHC engagement positively influences users' Paid in OHCs.

The Mediating Effect of User Online Health Communities Engagement

The previous research has suggested that when users frequently engage in online communities, they may gain a sense of belongingness, which in turn increases the possibility that they pay for online services (Brettel et al., 2015; Meng et al., 2020). Thus, we can regard Paid as a deeper level of engagement. Based on H1 and H2, it is reasonable to assume that health privacy information concerns (PICs) may influence Paid in OHCs. Intuitively speaking, lower-level engagement should serve as a transitional phase for deeper engagement (e.g., Paid). For instance, you won't know how to run unless you know how to walk. Therefore, it is reasonable to postulate that OHC engagement plays a mediating role in the relationship between users' health information privacy concerns and their Paid in OHCs. To this end, we hypothesize the following:

> *Hypothesis 3* (H3): Health information privacy concerns have a negative relationship with users' Paid in OHCs, mediated by their OHC engagement.

The Moderating Effects of Benefit and Threat Appraisals

On engaging in online communities, the users can obtain multiple benefits, such as increased convenience in daily life activities, a sense of self-value, and enjoyment (Heravi et al., 2018). These merits may influence users' degree of engagement, which could moderate the relationship between health information privacy concerns and OHC engagement. The users may have different motivations for using OHCs, where seeking social support (i.e., informational and emotional support) is the priority instead of monetary rewards (Mirzaei and Esmaeilzadeh, 2021). This is easy to understand since money can never buy health. Informational support refers to the possibility for OHC users to search for health information, suggestions on health issues, and timely medical help in a convenient, efficient, and effective manner (Wang X. et al., 2020). Emotional support refers to the possibility for OHC users to gain valuable insights from individuals in similar situations, which could reduce their stress and loneliness, cultivate a positive attitude, and help them develop self-value and self-efficacy (Gibbs et al., 2016). Although deeper privacy concerns may reduce users' willingness to share their sensitive health information (Dinev and Hart, 2005) and may lead to a lower degree of engagement, an individual's evaluation of potential benefits could have a significant moderating effect on this negative relationship. The previous research has suggested that people may act less rationally when carrying out a benefit–threat analysis (Barth et al., 2019; Jang and Sung, 2021) and often overestimate benefits (Manago and Melton, 2019). For example, when we are so enthusiastic for a new dress, we may only see how good the dress is, ignoring the fact that we may already have a lot of them in similar style, which leads to irrational purchase. This lack of rationality paves the way for analyzing the moderating effect from the perspective of users' BA. Specifically, users who perceive the benefits of information-sharing and emotional support in OHCs to be higher tend to have lower privacy concerns regarding OHC engagement. Thus, we propose the following hypothesis:

> *Hypothesis 4a* (H4a): Users' BA (i.e., perceived benefits of informational and emotional support in OHCs) increase the likelihood that users with high health information privacy concerns will engage in OHCs.

Threat appraisals (which negatively moderate the relationship between health information privacy concerns and OHC engagement) comprise two dimensions: perceived severity and perceived vulnerability of information disclosure. The former relates to the seriousness of the consequences of a potential data misuse, as evaluated by the user; the latter refers to the self-evaluation of the possibility of data misuse (Rogers, 1975; Zhang et al., 2017). First, a higher perceived severity means greater expected seriousness. Privacy violations may result in negative consequences like discrimination as well as social stigma (Crossler and Bélanger, 2019; Pettinico et al., 2020; Slepchuk et al., 2022), some of which can be severe. Users tend to adjust their level of engagement based on the perceived severity of potential privacy violations (Zhang et al., 2017; Barth et al., 2019). They are inclined to be more prudential when perceived severity remains at a higher level (Dinev and Hart, 2005; Herath et al., 2014). In other words, people may be less involved in OHC when the consequences are deemed too severe to bear. Second, a higher perceived vulnerability indicates that users believe they are more prone to privacy violations—that is, that their data are likely to be misused. Accordingly, users will take protective measures to reduce the expected threat and become less active in OHCs (Liu et al., 2017; Barth et al., 2019). Thus, it is reasonable to assume that both perceived severity and vulnerability (which comprise OHC users' TA) amplify the negative relationship between the health information privacy concerns and the

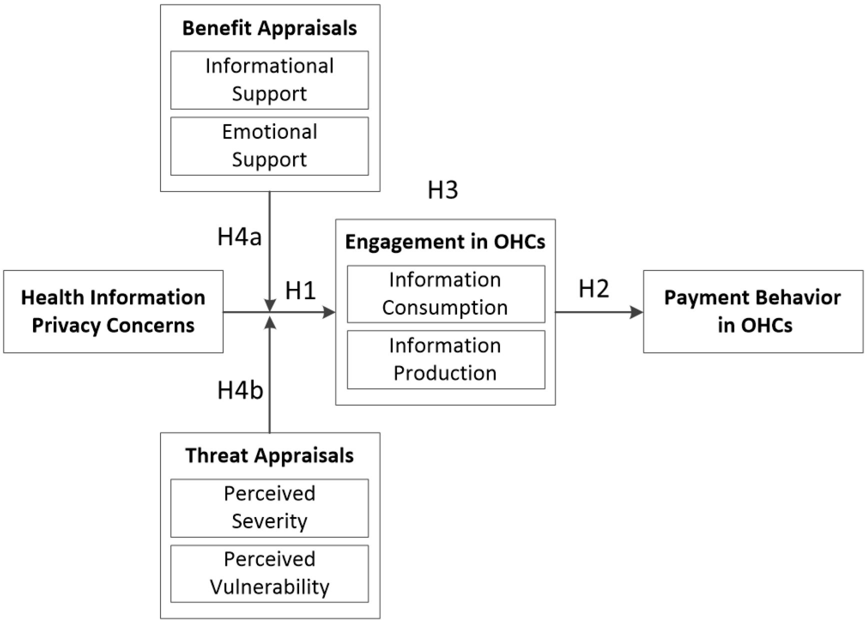

FIGURE 1 | Theoretical model.

users' OHC engagement. In other words, the users who have greater expected seriousness or believe they are more prone to privacy violations will be less active in OHCs. Thus, we posit the following hypothesis:

> *Hypothesis 4b* (H4b): Users' TA (i.e., perceived severity and vulnerability of information disclosure in OHCs) decrease the likelihood that users with significant health information privacy concerns will engage in OHCs.

Figure 1 shows the theoretical model of this study based on its theoretical framework and research hypotheses.

RESEARCH DESIGN

Data Source

For this study, we designed a questionnaire and uploaded it to the online platform, Credamo. Credamo is a data platform committed to providing solutions for large-scale research, data collection, modeling analysis, and commercial applications for scientific research institutions, enterprises, and individuals. Credamo provides scientific research and educational data services for teachers and students in more than 1,800 universities worldwide. The scope of services covers various disciplines such as management, psychology, medicine, sociology, tourism, and hotel management, while its research studies are accepted by top academic journals. Credamo also provides large-scale research, government affairs management, human resource management, consumer product development, and other information services for both governments and enterprises.

Note that all the data for the present study were collected from Credamo, where data representativeness is guaranteed because of Credamo's unique sampling method and comprehensive register of users, which covers all provinces, cities, and regions in China and most of their occupations. **Table 1** presents the sample statistics.

The questionnaire design process was divided into two stages. First, we sent the questionnaire to experts, who made suggestions on its design. After receiving their feedback, we optimized and modified the questionnaire and developed a final version. Second, we uploaded the questionnaire to Credamo

TABLE 1 | Sample characteristics ($N = 480$).

Variable		Count	Percentage (%)
Health conditions (HC)	Very poor	14	2.91
	Poor	130	27.03
	Fair	267	55.72
	Good	69	14.35
Age	<20	37	7.71
	20–29	241	50.21
	30–39	156	32.5
	40–49	32	6.67
	≥50	14	2.92
Education	Primary school or below (=1)	1	0.21
	Junior high school (=2)	3	0.62
	High school (=3)	22	4.57
	College Degree (=4)	52	10.81
	Bachelor degree (=5)	349	72.77
	Master degree (=6)	51	10.60
	Ph.D degree (=7)	2	0.42
Gender	Male (=1)	192	40
	Female (=0)	288	60

and collected users' answers. Specifically, the final version of the questionnaire comprised four parts. The first section details the purpose of the questionnaire, emphasizing that data collection is purely conducted for academic purposes, and guarantees the absolute confidentiality of the information. Then, we confirm whether the applicant has previously used OHCs. If not, the survey ends directly, which allows us to ensure the reliability of the results. Next comes the core section, collects data on UE in OHCs, including "views on filling in personal health information," "views on personal health information leakage," "specific usage behaviors," and "the possibility of paying for online medical consulting." Finally, we asked the participants to fill in their demographic information such as gender, education level, and health status. The constructs and corresponding items are outlined in the first two columns of **Table 2**.

To accurately identify the impact of privacy concerns on users' participation in OHCs, the model incorporates many control variables. Considering that factors such as age, educational level, gender, and health status may impact the relationship between privacy concerns and OHC engagement, we incorporated them into the model as control variables. The introduced control variables were consistent with those in the existing literature.

Measurement Assessment

Before identifying the structural model and testing for mediating and moderating effects, several tests were carried out to ensure the validity of the data. First, the standardized loadings of each item on the construct were computed, as shown in the third column of **Table 2**. We may safely draw the conclusion that the item reliability of all measures is good because all standard loadings are greater than 0.7 (Fornell and Larcker, 1981). Second, the average variance extracted values were calculated, and all four values were greater than 0.5 (Fornell and Larcker, 1981). Third, we derived composite reliability and Cronbach's alpha. All the values are greater than 0.7 (Hair et al., 2011), indicating the internal consistency and reliability of the measures. Combining the results of the four tests mentioned (see **Table 2**), we can conclude the validity of the data.

EMPIRICAL RESULTS

Correlation

To exclude the influence of multicollinearity, we derived the correlation matrix; the results are shown in **Table 3**. Note that we only show the correlation coefficients. Multicollinearity exists only when the coefficient is greater than 0.5 and is statistically significant. **Table 3** shows that no coefficients satisfied this condition, indicating that no multicollinearity effects exist in the model. Additionally, consistent with the intuitive negative relationship between UE and their Paid, the correlation coefficient between the UE and Paid is positive. Variance inflation factors (VIFs) were calculated to test for other potential multicollinearity problems. The maximum VIF obtained in any of the models was 4.23 and the mean VIF of the complete model [i.e., Model (4) in **Table 4**] was 3.38, which was substantially below the rule-of-thumb cutoff of 10 for regression models (Ryan, 1997). Therefore, multicollinearity was not considered an important issue in these analyses.

Main Effect

This study employs the ordinary least squares method (OLS) to test the relationship between users' health information privacy concerns and their engagement in OHCs. The results are shown in Models (1) and (2) of **Table 5**. Model (1) only incorporates the control variables. Model (2) adds the dependent variable PIC and shows that the effect of PIC on UE is significantly negative ($\beta = -0.199$, $p < 0.001$). Therefore, H1 (health information privacy concern negatively influences UE in OHCs) is supported.

Since Paid is a dichotomous variable, we use a logit model to test the relationship between user OHC engagement and Paid. The results are shown in Models (3) and (4). Model (3) is the baseline. Model (4) shows that the coefficient of UE is positively significant ($\beta = 1.316$, $p < 0.001$). Therefore, H2 (OHCs engagement positively influences users' Paid in OHCs) is supported.

The coefficients of the control variables show that a higher degree of engagement exists for users who are male and older.

Mediating Effect

We refer to the method of Baron and Kenny (1986) and conduct three-step econometric models to test the mediating model. The first step examines whether health information privacy concerns have an impact on user OHC engagement (i.e., PIC → UE). The results in Model (2) of **Table 5** support this relationship. The second step examines whether UE in OHCs has an impact on their Paid (i.e., UE → Paid). The results in Model (4) of **Table 5** support this.

Based on these results, the third step examines the relationship between health information privacy concerns and users' Paid (i.e., PIC → Paid). Model (5) shows that the effect of PIC on Paid is significantly negative ($\beta = -0.452$, $p < 0.01$). After incorporating the mediating variable UE in Model (5), the coefficient of UE is still significant at the significance level of 0.001, while the marginal effect of UE on Paid changes from -0.452 to -0.241, and becomes insignificant ($p > 0.05$). The results indicate that user OHC engagement plays a fully mediating role in the impact of health information privacy concerns on users' Paid, supporting H3.

Moderating Effects

To test the moderating effect of BA and TA on the relationship between users' health information privacy concerns and their OHC engagement, we add the interaction term between health information privacy concerns and BA (i.e., PIC × BA), as well as the interaction term between PIC and TA (i.e., PIC × TA) into the regression model. The results are shown in **Table 4**.

Models (2) and (4) show that the impact of PIC × BA on UE is positive at the significance level of 0.01, indicating that users' BA positively moderate the relationship between health information privacy concerns and users' OHCs engagement. Thus, H4a is supported. In addition, the coefficient of PIC × TA is negative at the significance level of 0.01, which supports H4b that

TABLE 2 | Research constructs, measurements, item loadings, and validities.

Construct	Item	Standard Loading	AVE	CR	Cronbach's Alpha
PIC (privacy information concern)	(1) I feel that it is not advisable to fill in personal health information in the online health community	0.847	0.714	0.882	0.853
	(2) Once the personal health information in the online health community is filled in, it will be abused by companies	0.840			
	(3) Once the personal health information in the online health community is filled in, it will be shared by the company or sold to others	0.848			
BA (benefit appraisals)	(1) When I need help in the online health community, someone will give me advice	0.851	0.736	0.916	0.871
	(2) When I encounter difficulties, users in the online health community will help me find the reasons and provide suggestions	0.846			
	(3) When I encounter difficulties, users in the online health community will comfort and encourage me	0.859			
	(4) When I encounter difficulties, users in the online health community will express their concern for me	0.863			
TA (threat appraisals)	(1) Personal health information in the online health community is at risk of being shared or sold	0.850	0.724	0.887	0.913
	(2) My personal health information in the online health community may be shared or sold	0.852			
	(3) Once I fill in my personal health information in the online health community, my information may be shared or sold	0.851			
UE (user engagement)	(1) I will share my treatment process in the online health community	0.870	0.710	0.907	0.755
	(2) I will make comments on the doctor in the online health community	0.793			
	(3) I will "like" other users' contents in the online health community	0.893			
	(4) I will recommend the online health community to my friends	0.711			
PB (payment behavior)	Have you ever paid to doctors for medical consultations in the online health community?				

users' TA increase the likelihood for users with significant health information privacy concerns to engage in OHCs.

Figure 2 shows the moderating effects more intuitively. We added and subtracted a standard deviation on BA and TA and further drew on the relationship between PIC and UE at the different levels of BA or TA. The analysis logic of the two graphs is similar, and both focus on the steepness of the line. As shown on the left side of **Figure 2**, when BA changed from BA – SD to BA + SD, the line becomes flattener, and the absolute value of the slope decreased, indicating that users' BA positively moderate the negative relationship between users' health information privacy concerns and their OHCs engagement. The right side of **Figure 2** shows that when TA changed from TA − SD to TA + SD, the line becomes steeper, indicating that users' TA negatively moderate the relationship between users' health information privacy concerns and their OHC engagement.

DISCUSSION AND CONCLUSION

Conclusion

This study explores the impact of users' health information privacy concerns on their engagement and Paid in OHCs, as well as the moderating effects of users' benefits and TA of sharing information. There are three main conclusions. First, we indicate a negative relationship between users' health information privacy concerns and their OHC engagement. The higher users' health information privacy concerns, the lower their OHC engagement. Second, after analyzing Paid in the context of OHCs, we find that UE in OHCs mediates the relationship between users' health information privacy concerns and their Paid in OHCs. That is, health information privacy concerns affect users' Paid by influencing their OHC engagement. Third, we identify the moderating effects of BA and TA on the negative relationship between health information privacy concerns and user OHC engagement. Benefit appraisals of using OHCs increase the likelihood that individuals with high health information privacy concerns would engage in OHCs, while TA will decrease the likelihood that individuals with high health information privacy concerns would engage in OHCs.

Theoretical Contributions

Our study's theoretical contributions can be summarized as follows. First, it extends the existing literature on the antecedents of UE in OHCs by incorporating health information privacy concerns into its analysis. Extant research has identified the

TABLE 3 | Correlation matrix.

Variables	1	2	3	4	5	6	7	8
1 Paid user								
2 UE	0.411*							
3 PIC	−0.274*	−0.369*						
4 BA	−0.131*	−0.06	0.301*					
5 TA	−0.260*	−0.334*	0.703*	0.452*				
6 HC	−0.08	0.04	−0.01	0.00	0.00			
7 Gen	0.115*	0.146*	−0.06	−0.06	−0.092*	0.03		
8 Age	0.116*	0.145*	−0.01	−0.06	−0.091*	−0.106*	0.096*	
9 Degree	−0.04	0.02	0.05	0.04	0.124*	0.093*	−0.03	−0.187*

*$p < 0.05$.

TABLE 4 | Results of the moderating effects.

	UE			
	(1)	(2)	(3)	(4)
PIC	−0.199***	−0.486***	−0.524***	−0.652***
	(0.042)	(0.136)	(0.137)	(0.163)
PIC × BA		0.072**		0.075**
		(0.032)		(0.035)
PIC × TA			−0.085**	−0.066**
			(0.034)	(0.032)
BA	0.068**	−0.094	0.077**	−0.037
	(0.034)	(0.081)	(0.034)	(0.086)
TA	−0.114**	−0.100**	−0.288***	−0.241**
	(0.039)	(0.039)	(0.080)	(0.086)
HC = Poor	0.157	0.189	0.186	0.202
	(0.183)	(0.182)	(0.182)	(0.182)
HC = Fair	−0.183	0.209	−0.322	−0.789
	(0.719)	(0.178)	(0.727)	(0.819)
HC = Good	0.135	0.170	0.164	0.182
	(0.188)	(0.188)	(0.188)	(0.188)
Gen = Male	0.179**	0.168**	0.174**	0.167**
	(0.059)	(0.059)	(0.059)	(0.059)
Age	0.101**	0.097**	0.097**	0.095**
	(0.035)	(0.035)	(0.035)	(0.035)
Education fixed effect	Control	Control	Control	Control
City fixed effect	Control	Control	Control	Control
Constant	0.862	0.805	1.282**	1.456**
	(0.629)	(0.643)	(0.647)	(0.658)
N	480	480	480	480
Adjusted R^2	0.215	0.222	0.224	0.226

*Standard errors in parentheses; **p < 0.01, ***p < 0.001.*

TABLE 5 | Results of the main and mediating effects.

	UE		Paid			
	OLS		Logit model			
	(1)	(2)	(3)	(4)	(5)	(6)
PIC		−0.199***			−0.452**	−0.241
		(0.042)			(0.158)	(0.172)
UE				1.316***		1.267***
				(0.191)		(0.194)
BA	−0.083	0.068**	0.074**	−0.250	−0.095	−0.250
	(0.154)	(0.034)	(0.035)	(0.173)	(0.156)	(0.173)
TA	−0.610***	−0.114**	−0.238***	−0.223	−0.325**	−0.223
	(0.130)	(0.039)	(0.030)	(0.178)	(0.165)	(0.178)
HC = Poor	−0.148	−0.271	0.191	−0.565	0.157	−0.590
	(0.743)	(0.750)	(0.187)	(0.841)	(0.183)	(0.843)
HC = Fair	0.209	0.237	0.249	−0.752	0.238	0.251
	(0.178)	(0.177)	(0.181)	(0.818)	(0.177)	(0.177)
HC = Good	−0.769	0.135	0.162	−1.249	−0.887	−1.284
	(0.752)	(0.188)	(0.193)	(0.852)	(0.760)	(0.854)
Gen = Male	0.499**	0.179**	0.177**	0.287	0.532**	0.319
	(0.245)	(0.059)	(0.060)	(0.265)	(0.249)	(0.267)
Age	0.271*	0.101**	0.090**	0.131	0.309**	0.147
	(0.147)	(0.035)	(0.036)	(0.151)	(0.148)	(0.152)
Education fixed effect	Control	Control	Control	Control	Control	Control
City fixed effect	Control	Control	Control	Control	Control	Control
Constant	1.590	0.862	(0.643)	−2.640	1.688	−2.421
	(1.762)	(0.629)	480	(1.930)	(1.759)	(1.931)
N	480	480	480	480	480	480
Adjusted R^2	0.095	0.215				
Pseudo R^2			0.179	0.198	0.111	0.203

*Standard errors in parentheses; *p < 0.05, **p < 0.01, ***p < 0.001.*

antecedents of OHC engagement, and to gain informational support, as well as emotional support, are considered the primary motivations (Ray et al., 2014; Gibbs et al., 2016; Yan et al., 2016; Wang et al., 2017). Safety concerns related to the ongoing COVID-19 pandemic have also fostered enthusiasm for engagement in OHCs (Huang et al., 2021). However, to the best of our knowledge, few studies have been conducted on the impact of information privacy concerns on user engagement. Actually, health information is highly sensitive and requires high accuracy (Markos et al., 2018), which is significantly different from the information in other online communities (Kopalle and Lehmann, 2021). Thus, conclusions in other online communities cannot be applied directly in the context of OHCs. Considering the severe consequences of data breaches, the importance of privacy concerns should not be ignored in users' decisions to participate in OHCs.

Second, this study sheds light on users' Paid in OHCs. On the one hand, previous research has mainly discussed UE in OHCs, whereas Paid remains relatively unexplored. OHC users primarily search for health-related information (Wang X. et al., 2020) and professional online medical services (Huang et al., 2021), while aiming to communicate with individuals who have similar experiences (Chou et al., 2018). On the other hand, the scarce studies on Paid in online communities have not been carried out within the context of OHCs. Research on other online communities has shown that users are more inclined to pay for online services to gain stable socializing functions and entertainment value from online communities after they have become emotionally attached (Oestreicher-Singer and Zalmanson, 2013; Brettel et al., 2015; Meng et al., 2020). Thus, combining health information privacy concern and online Paid could provide valuable insights.

Third, this study deals with a research gap by incorporating BA and TA within the context of OHCs. The previous research has suggested that people may become less rational when carrying out benefit–threat analysis (Barth et al., 2019; Jang and Sung, 2021), in which they are inclined to overvalue the merits (Manago and Melton, 2019). The lack of rationality paves the way for analyzing the moderating effect from the perspective of users' benefits and TA. In contrast, users tend to be more prudential (Pluye et al., 2019) and may take protective measures to mitigate the expected threat by becoming less active in OHCs (Liu et al., 2017; Barth et al., 2019). Thus, elucidating the effects of benefit and threat appraisal is of great significance to understand OHC engagement.

Practical Implications

The practical implications of this study can be summarized as follows. For OHC administrators, at least two objectives

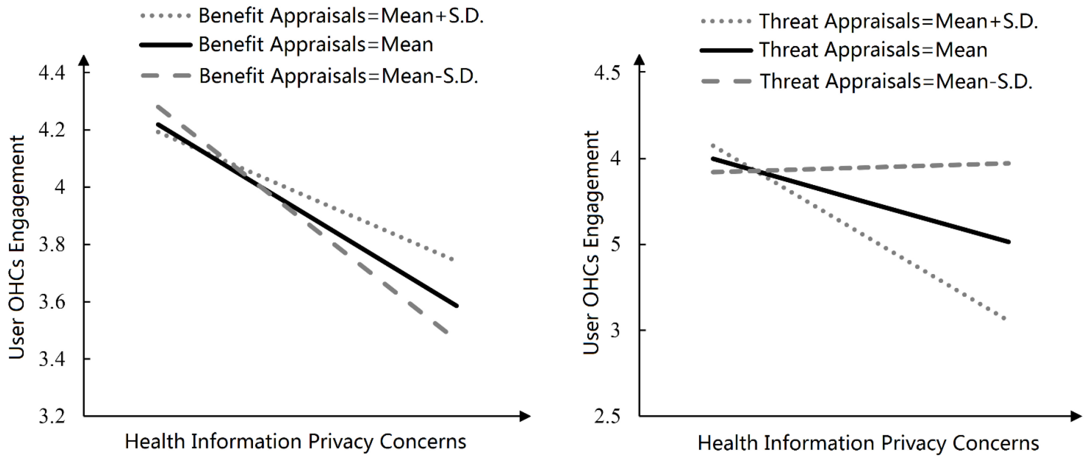

FIGURE 2 | Interaction graphs.

are elucidated in this study. First, they should aim to guarantee the protection of users' private information. This study shows that the more concerned users are about their health information privacy, the lower their engagement in OHCs. Thus, OHC administrators should reduce users' privacy concerns to foster the long-term development of OHCs, since OHCs are information sharing or information-driven platforms. Specifically, administrators could provide users with more options for information disclosure and increase transparency by informing users why and how their information will be used. Second, administrators should improve users' stickiness and cultivate their sense of belonging. This study suggests that health information privacy concerns affect users' Paid *via* their engagement in OHCs. Intuitively, if a higher proportion of users is willing to pay for services, the platform will reap higher profits; thus, OHC administrators should introduce more measures to increase UE and gradually cultivate their loyalty and sense of belongingness to the platform, which will, in turn, increase the possibility that they will pay for online services (Brettel et al., 2015; Meng et al., 2020).

Additionally, there is one meaningful implication for users. This study indicates that people who perceive the benefits of informational and emotional support from OHCs to be higher tend to engage more frequently in OHCs. In contrast, individuals who perceive the threats inherent to information disclosure to be higher reduce their OHC engagement. The previous research has suggested that people may act less rationally when carrying out benefit-threat analyses (Barth et al., 2019; Jang and Sung, 2021). Thus, users should act rationally and not overestimate or underestimate the perceived benefits and threats, thereby developing reasonable expectations for the support provided in OHCs, which could allow them to obtain a better user experience.

Limitations and Further Research

This study has some limitations that can also provide promising directions for future research. First, the effect of differences in medical service quality should be considered, as the unbalanced distribution of medical resources caused by geographical dispersion influences UE in OHCs. Although the questionnaire designed in this study collected users' geographic information, it did not analyze these data *vis-à-vis* the distribution of medical resources or its heterogeneity effect. China has a vast territory, and the distribution of medical resources is highly uneven. The previous studies have shown that OHCs could narrow the quality gap of medical services between urban and rural areas (Goh et al., 2016; Cao and Wang, 2018). Thus, it would be valuable to conduct more research on how medical conditions influence the decision of users with high health information privacy concerns regarding OHC engagement.

Second, the effect of the size of OHCs. Larger communities have more stable cash flows and, in turn, are less likely to suffer data breaches. Additionally, they often have more advanced technology to protect users' data from being hacked. Thus, OHCs' size may moderate the relationship between PICs and user engagement, which requires further exploration in future studies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

ETHICS STATEMENT

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the (patients/participants or patients/participants legal guardian/next of kin) was not required to participate in this study in accordance with the national legislation and the institutional requirements.

AUTHOR CONTRIBUTIONS

BW designed the research framework. PL carried out the survey. ML and XH analyzed the data. BW, PL, XH, and ML wrote the manuscript. BW and PL contributed equally to the manuscript. All authors contributed to the article and approved the submitted version.

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The Impact of Beliefs on Health Information Social Sharing for Users: The Perspectives of Social Psychology and Information Technology

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With the integration and penetration of digitization into healthcare services, the comprehensive health industrial market is developing flourishingly. Users are fast-changing the way of health communication. This study investigates psychosocial and technological factors on health information sharing adoption through social sharing services. Based on the unified theory of acceptance and use of technology, social influence theory, and innovation diffusion theory, we developed a hypothesized model for health information social sharing adoption (HISSA), and dimensions of attitude beliefs, control beliefs, and normative beliefs were created. We conducted an empirical study on the adoption intention using a survey for data collection. The results were obtained from 375 valid questionnaires, and their interactions were tested and analyzed using PLS-structural equation modeling. Results implied that (1) social identity of normative beliefs was the most critical variable affecting behavioral intention, which revealed the importance of psychosocial factors; (2) behavioral intention was also determined by user's performance expectancy, facilitating conditions, subjective norm; (3) personal innovativeness had a negative effect on behavioral intention and positive effect on effort expectancy; and (4) effort expectancy and social identity had a positive effect on performance expectancy. This study advances the understanding of social sharing for health and provides references for the development of both virtual health communities and social sharing services to upgrade their products from user's behavior and psychology. This empirical research model may also be useful for researchers who are interested in user's health information behavior.

Keywords: health information social sharing, UTAUT, normative beliefs, adoption intention, virtual health communities

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INTRODUCTION

Entering the 21st century, the pursuit of human beings has changed from developing economy to caring for their health; health and medical informatization became constant popularity. With the advent of the mobile Internet era, social media was applied globally, especially in the healthcare context. Since the coronavirus disease 2019 (COVID-19) outbreak, social media played a vital role in disseminating information about the pandemic. Health information was posted in text and in more easily accessible and diffusible forms through social media (Li et al., 2018). Recently, an emerging service "social sharing" has greatly changed the nature and speed of health information interaction on social media. People were enabled to share health information to single or multiple communities through hyperlinks. For instance, a social media user could click the "share button" to share the popular science article "*The First Symptom of Novel Coronavirus Pneumonia May Be Olfactory or Taste Abnormalities*" from BBS.DXY.CN, a health information community, with her fellow wards on WeChat or QQ ZONE immediately. Since 2011, more than 50% of websites used social sharing tools around the world.

Health information social sharing provides opportunities for health knowledge among multiusers through multisensory communication (Moorhead et al., 2013). This benefits both the health community and its users. From the viewpoint of users, the share function of social sharing services maximizes health content and dissemination of information. Health information social sharing would strengthen the awareness of healthcare and the attention to their body condition. For example, people repost epidemic data to their circle to see if destinations are suitable for travel *via* health information social sharing and share action trajectory of suspected cases as a precaution (Pham et al., 2020). Health social sharing enables people without a professional background to distribute health information easily and rapidly, considering health information is characterized by professionalism and a high comprehension threshold. Thus, it has high use value and great potential to affect public health status. From the viewpoint of a health virtual community, health information social sharing diversified the way through which information content can be shared and converted its large base of inactive users into active ones, as well as let them keep surfing the web (Liu et al., 2018). Thus, health information social sharing promotes them to develop vigorously.

Previous literature has considered sharing health information from information technology (IT) perspective, mainly focusing on design and construction of the platform, influencing factors of health information sharing on social networking site (SNS) and virtual community (Fan et al., 2015; Zhang, 2018; Xia et al., 2021), etc. However, limitations still exist. Despite the extensive offer and the obvious potential benefits of health information social sharing, what motivates the adoption was still ambiguous. Health information social sharing was determined by the use of service and speed of adoption. Therefore, modeling user adoption behavior was necessary. Models about user adoption were established at the technological level in previous studies, but they were not comprehensive. We found that previous research models did not pay enough attention to the psychosocial factors on users and their sharing process, such as how individuals can better express and learn health knowledge through social sharing, how they are influenced by others when sharing health content, and why some users are willing to share with others and under what circumstances they are not willing to share. This results in the lack of sufficient explanatory power and one-sidedness of the research on health sharing adoption and its influencing factors that the limitations then caused frictions between theory and practice on the complex behavior psychology of users. Consequently, to fill the gap mentioned above, on the basis of existing studies, the theoretical investigation and model analysis of user adoption behavior in health information social sharing need to be further improved. This study aims to investigate factors on user's adoption intention of health information social sharing. The hypothetical model is proposed in dimensions of attitude beliefs, control beliefs, and normative beliefs to reveal the internal influence mechanism. This study advances the understanding of social sharing for users and reflects the combination of healthcare and emerging technologies, as well as provides insights for the development of both virtual health communities and social media.

This study is structured as follows. After the introduction, "Background and Research Hypotheses Development" section refers to the background and research hypotheses development. In the "Materials and Methods" section, we addressed materials and methods. The "Results" section is dedicated to the data analysis and results. This is followed by the "Discussion" section and the "Conclusion" section, respectively.

BACKGROUND AND RESEARCH HYPOTHESES DEVELOPMENT

Background Literature

The Theory of Planned Behavior (TPB) is one of the most applied theories in the social and behavioral sciences. According to TPB, human action is guided by three kinds of considerations, namely, behavioral beliefs, normative beliefs, and control beliefs (Ajzen, 1991). Behavioral beliefs refer to beliefs about the likely outcomes of the behavior and the evaluations of these outcomes. Normative beliefs express the normative expectations of others, and control beliefs discuss the presence of factors that may facilitate or impede performance of the behavior and the perceived power of these factors. The TPB has received broad attention in the field of health sciences, environmental science, business and management, and educational research in recent years (Downs and Hausenblas, 2005; Yang, 2012; Adnan et al., 2017; Karimi and Makreet, 2020). Tomczyk et al. (2020) suggested that future research should apply more extensive measures of the TPB and other health behavior models, for example, regarding intentions or willingness.

Combining technology acceptance theories and behavior intention theories, Venkatesh et al. (2003) integrated 32 original constructs to get four component variables and four controlled variables. Then, a unified model named the Unified Theory of Acceptance and Use of Technology (UTAUT) was formulated (see **Figure 1**). As a popular theoretical model within the field of information technology, UTAUT includes constructs and relationships specific to an IT context, contributing to capturing the technology-related attributes and specific technology-generated environments (Castañeda et al., 2019). This model includes three variables (i.e., performance expectancy (PE), effort expectancy (EE), and social influence) that have positive effects on behavioral intention to use a technology, one

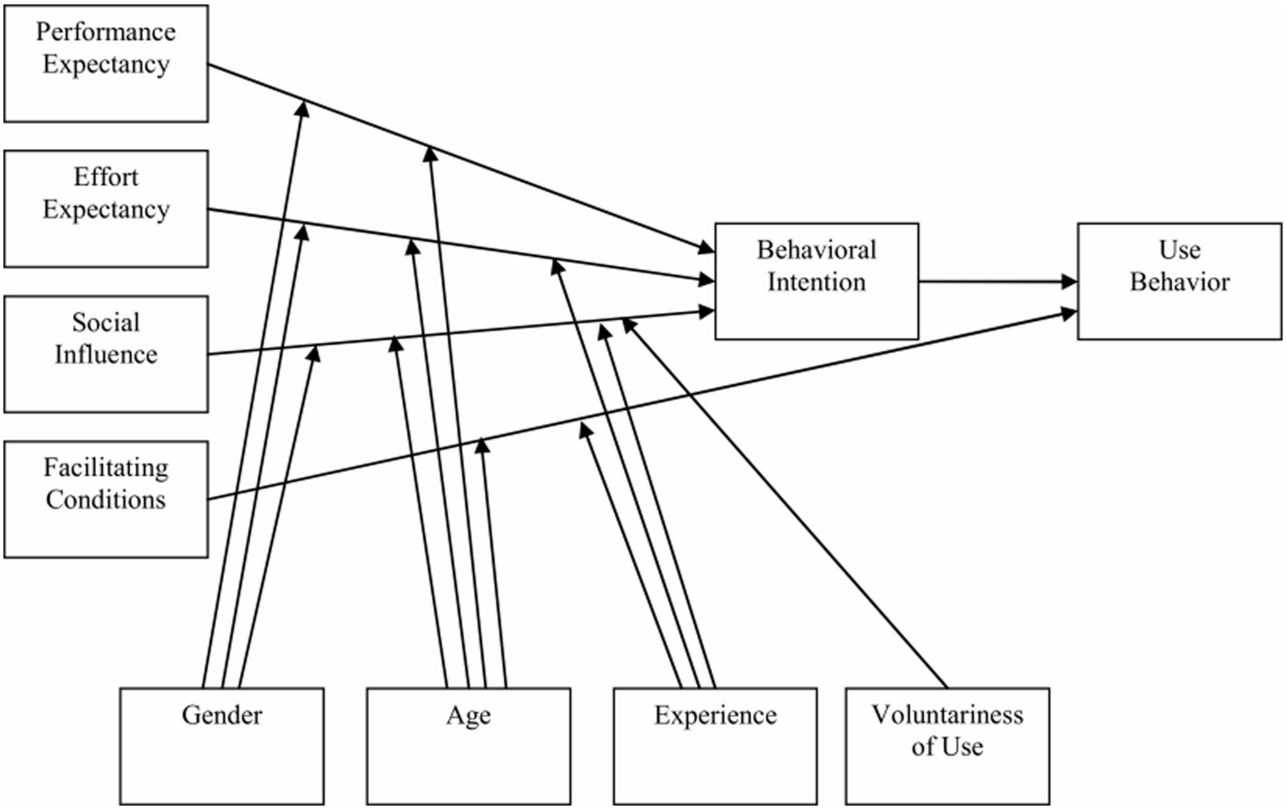

FIGURE 1 | The unified theory of acceptance and use of technology.

variable [facilitating conditions (FCs)] that affects actual usage, and the adoption intention has a significant impact on user behavior (Venkatesh and Davis, 2000). Mpinganjira (2019) found that UTAUT can be appropriate for medical and health fields through research on factors of willingness to reciprocate in virtual health communities. Zhang et al. (2018) discussed factors on user medical information behavior in online health communities based on UTAUT. Although the model of UTAUT was originally devised to be used in the context of information technology acceptance as a universal model, which intended to be a timesaver for researchers to understand various theoretical models. After compiling 450 pieces of literature based on UTAUT, studies showed that the majority of research sought to combine UTAUT with other theories and constructs or used only partial constructs of this model (Williams et al., 2012). It seems that UTAUT cannot understand emerging scenarios any better. Venkatesh also pointed out that UTAUT was bound to have an even broader prospect for development. Thus, considering its characteristics, UTAUT should be modified in the context of health information and social sharing.

Social influence was a common social psychological phenomenon in people's lives, which refers to the use of the external role of individuals or groups to cause the change of individual thoughts, attitudes, and behaviors in a specific direction. Social Influence Theory (SIT) explained the antecedent variables of opinion formation and changes (Huang et al., 2013). The theory assumed that if attitudes based on different motives were adopted in different social impact situations, their qualitative characteristics and final behavior would be different (Kelman, 1958). Cheung and Lee (2010) used social networking sites together to explain in terms of the three social influence processes, namely, subjective norm (SN), group norm (GN), and social identity (SI). Even though, UTAUT integrated the construct of psychosocial factors from classic models and then develop social influence. Apparently, whether its definition or the questions, Venkatesh used to reflect that social influence remains in the category of SN and hardly contains its three mechanisms. Thus, the impact of social influence needs to be further improved.

Innovation diffusion theory (IDT) provides the theoretical basis for this study as well. It mainly describes the diffusion process of innovation in the social system. Rogers (2010) pointed out that individuals with high innovativeness had some behavioral characteristics such as actively searching for information, more public media exposure, and less dependent on the subjective evaluation of other members of the group. Many academics, practitioners have been focused on IDT after its proposition and spread-related research immediately, including research on the diffusion and process at the macro level and research on innovative adoption at the micro level

(Wang and Chen, 2012). The innovativeness is an important factor to predict IT innovation adoption (Agarwal and Prasad, 1998). In recent years, IDT has been used to study users' adoption of new healthcare information technologies. Zhang et al. (2015) examined the major factors influencing patients' acceptance and use of the e-appointment service through the theoretical lens of Rogers' IDT. Jiang and Luan (2018) did a comparative study of Chinese and US pharmaceutical patents through the lenses of IDT approach and using network analysis and visualization techniques.

Combining the existing literature to sort out the detailed connotation and the application of the model and theory, according to the context of this study, influencing factors on health information social sharing adoption (HISSA) are divided into three dimensions, namely, attitude beliefs, control beliefs, and normative beliefs.

Attitude Beliefs for Health Information Social Sharing

Attitude beliefs refer to a favorable or unfavorable attitude that behavioral beliefs (beliefs about the likely outcomes of the behavior and the evaluations of these outcomes) produce. We classified attitude beliefs into two variables due to their connotations and attributes. As one of the UTAUT's six main variables, performance expectation (PE) is a new concept integrating the perceived usefulness of Technology Acceptance Model (TAM) and the extrinsic motivation of the Theory of Motivation. Personal innovativeness (PI) is relevant to personal attitude; it refers to the degree to which a person believes that he/she is positively predisposed toward the use of new technologies (Agarwal and Prasad, 1998).

Performance expectancy is the perceived usefulness of adopting a system and the belief that the use of the adopted system will aid them in their job performance. (Brown et al., 2016) has been proved to significantly determine whether users accept the product in the context of social media. However, there is still less known about the impact of PE on social network technology and services, especially in sharing health information. Health information social sharing aims to simplify sharing procedures and improve health sharing efficiency. It would enhance their intention to use when thinking it can fulfill their demand of share, mainly reflected in how often they share valuable health information using social sharing services and how willing they are to communicate and share with their community members. Therefore, this study hypothesizes that:

> Hypothesis (H1). PE positively affects the behavioral intention (BI) in health information social sharing.

The construct of PI was used to predict IT adoption intention, especially in the healthcare field such as patients' acceptance of consumer e-health, usage of mobile health applications, and school health education (Zhang et al., 2015; Gharaibeh et al., 2020). The adoption intention of innovativeness might be distinct due to the differences in innovativeness among individuals under the IDT (Brown et al., 2016). Karahanna and Chervany (2016) found out that people with a higher level of PI have a lower perception of difficulties in using the new system than other users. Another construct, the EE, reflects the new users' perception of system ease of use. Lewis and Sambamurthy (2003) suggested that PI had an influence on beliefs about ease of use in IT adoption. Walczuch et al. (2007) investigated the relationship between the personality attributes of employees and their use of IT support technology and found that PI had a significant influence on ease of use, employees with high PI felt less difficulty in using technology. Therefore, it can be supposed a relationship between the PI and EE in the health information sharing context. We expanded that relationship and considered that users with high PI have a much lower perception of use difficulty. In other words, their EE in social sharing services is high. Thus, we hypothesized that:

> Hypotheses (H2a). PI positively affects BI in health information social sharing.
> Hypotheses (H2b). PI positively affects EE in health information social sharing.

Control Beliefs for Health Information Social Sharing

Based on TPB, control beliefs are relevant to perceived behavioral control and are predicted to provide the basis for perceptions of behavioral control. We grouped EE and FCs into control beliefs because they stress perceptions of behavioral control as well as individual control capabilities while using a new IT product. EE is one of the determinants of technology acceptance. FCs come from the variable of perceived behavioral control of TPB.

Effort expectancy refers to the level of ease in adopting the use of a technology system and recognized as a critical predictor of BI in the context of social networks (Wong et al., 2015). If the cost of learning and usage in health information social sharing exceeds a certain level, users would be likely to reduce or even give up their intention. On the contrary, if a new technology of health sharing service requires less effort to learn and understand the way of using it, the adoption intention would be higher (Chua et al., 2018).

According to UTAUT, perceived ease of use refers to the labor-saving degree of service, which has a significant positive impact on perceived usefulness. Chiu and Wang (2008) found that EE significantly affected users' intention to continue using the online learning system and had a profound impact on users' PE. Thus, it can be inferred that EE affects PE; users' PE would be increased, while they have a higher EE of the service. According to the context of this study, when the cost of learning and the cost of using health information social sharing service is low, users are likely to form the perception that "this service is helpful to me." On the contrary, it may reduce user perception of the usefulness. Thus, we hypothesized that:

> Hypotheses (H3a). EE positively affects BI in health information social sharing.
> Hypotheses (H3b). EE positively affects PE in health information social sharing.

Facilitating conditions come from the variable of perceived behavioral control of TPB and is defined as the individual's belief about the support for the organization and technical facilities available when using the system. The study of Guan et al. (2012) has confirmed that FC could predict the intention of government officials to adopt microblog. Wilson and Lankton (2009) presented a rational-objective (R-O) model of e-health use that accounted for the effects of FC on predicting the use of e-health. According to this study, BI would ascend while people consider that they could get support for engaging in health information social sharing (e.g., devices and networks). On the contrary, their adoption intention would be decreased due to the lack of relevant conditions despite the demand for sharing health knowledge. Thus, we hypothesized that:

> Hypothesis (H4). FC in health information social sharing positively affects BI.

Normative Beliefs for Health Information Social Sharing

Ajzen pointed out in TPB that normative beliefs were beliefs about the normative expectations of others and motivation to comply with these expectations (Ajzen, 1991). According to the existing literature research results, we grouped media influence (MI), SN, and SI into normative beliefs.

Subjective norm refers to situations in which an individual's behavior is affected by the environment (Huang et al., 2008). Social psychologists pointed out that social networkers always tend to be consistent with the important someone (Pelling and White, 2009). SN significantly predicted intentions to engage in SNW use with intention significantly predicting behaviors. According to Zhao (2016), SN influences the continuance behavioral intention of Knowledge Question-and-Answer SNS users. According to the context of this study, users are more likely to be driven by others, and their sharing intentions related to healthcare are increased by then when their family and friends are sharing health information by using social sharing services or the important someone thinks they should do it. On the contrary, the idea of engagements with health information social sharing would be reduced or eliminated. Joseph and Jacob (2011) found in their study that SN had a strong impact on sharing knowledge intention. Thus, we hypothesized that:

> Hypothesis (H5). SN positively affects BI in health information social sharing.

According to Rogers' research on IDT, adoption decisions are driven by some second-hand information sources (e.g., TV and journal). Laumer et al. (2010) considered the MI as objective norm (ON) to distinguish MI from SNs and listed them as two different types of normative beliefs, laying the foundation that MI can be the same rank as the SN and SI. The construct of MI may be preferably used in customers' adoption literature. A few studies on IT adoption have discussed the prediction abilities of media influence, as the study of Venkatesh and Brown (2001) pointed out that household PC adoption decisions would be influenced by the messages conveyed *via* the mass media. Similar studies also appear in the adoption of health information. Griffith et al. (2012) noted in their study that the mass media can affect the way that African American men obtain, process, and use health information as well. According to the context of this study, stakeholders (e.g., content providers, sharing service providers, and social media) would affect adoption decisions by conducting the service propaganda through various channels. Thus, we hypothesized that:

> Hypothesis (H6). MI positively affects BI in health information social sharing.

Social identity derives from the user's interaction with others of his membership in a social group in the social networking environment. The motivation to establish and maintain SI would promote some online behaviors (Shen et al., 2011). Specifically, it has been suggested its importance of predicting the online social activity intention of SNS users besides SN in Cheung's study (Cheung and Lee, 2010).

Clément et al. (2001) have pointed out that users who collaborate with others to maintain their SI need communication support. Kwon and Wen (2010) have analyzed the relationship between SI and perceived ease of use in their research on social media adoption, and the empirical study indicates that SI has a significant positive impact on users' perceived ease of use. In the field of healthcare, psychologists suggest that SI support is exerted on attitudes, intentions, and health behavior (Chatzisarantis et al., 2009). According to the context of this study, it can be inferred that SI would influence the perceived usefulness while engaging in health information social sharing, i.e., SI is related to PE. Thus, we hypothesized that:

> Hypotheses (H7a). SI positively affects BI in health information social sharing.
> Hypotheses (H7b). SI positively affects PE in health information social sharing.

Based on the selection of the model variables above, this study inherits the core constructs of UTAUT and TPB considering the technological attributes of health information social sharing service and expanded it by combining the constructs and connotations of SIT and IDT considering that social sharing service was an emergent technological innovation with specific social attributes. Then, we developed a hypothesized model of health information social sharing adoption (HISSA) by integrating the interaction among dimensions of attitude beliefs, control beliefs, and normative beliefs and their constructs' effects on behavioral intention. The HISSA model is shown in **Figure 2**.

MATERIALS AND METHODS

Data Collection

This study uses questionnaires, which were conducted both through network questionnaires and paper questionnaires. Convenience sampling and Snowball sampling were used to select participants. Online questionnaires were posted and collected on "Wenjuanxing" platform (http://www.sojump.com/). Paper questionnaires were sent out in public places with high people flow (e.g., hospitals and banks) and in colleges and universities. Small gifts were given to participants before filling out the questionnaires for their participation. To ensure the quality and authenticity of the returned questionnaire, IP address

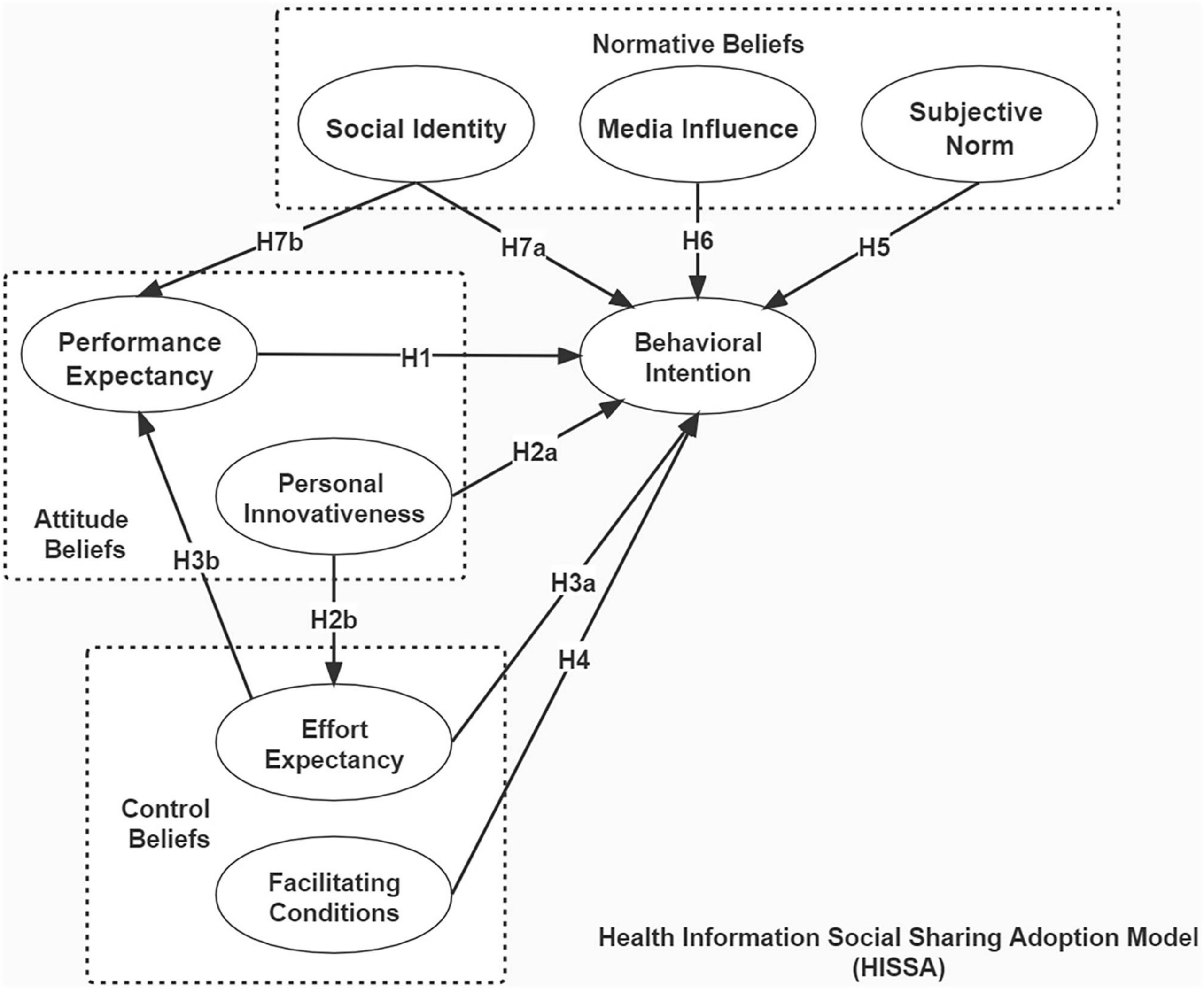

FIGURE 2 | The hypothesized model of health information social sharing adoption (HISSA).

recognition was set to reject the repeated submission of online questionnaires from the same address. The time control method was used to ensure the attitude of the respondents serious as well. Additionally, invalid paper questionnaires such as including too many "uncertain" options or the same answer for all questions were rejected.

The questionnaire lasted 42 days. In total, 263 online questionnaires were returned, of which 212 were valid, and 177 paper questionnaires were returned, of which, 163 were valid after excluding the invalid questionnaires. Finally, 375 valid questionnaires were collected in total with an effective rate of 85.2%.

The categorical variables of the 375 valid questionnaires included gender, age, education, occupation, and their use of social media and social sharing. Each variable corresponded to "The 47th Statistical Report on Internet Development in China" published by CNNIC. Notably, 82.6% of participants had social sharing 5 times or more per month. Participant description is provided in **Table 1**.

Measurement Instrument

The measurement items of this study were mainly adapted from the previous studies where all have been applied with sufficient validity. We adapted them for PE, EE, FC, PI, SN, MI, BI, and SI according to the actual situation of the research object and context. The scale came from scientific design principles proposed by Churchill. The measurement items of each construct consisted of no less than two questions (Churchill, 1979). The formal questionnaire came in three major parts, namely, questionnaire instruction, basic information, and use survey of health information social sharing service. More specifically, the questionnaire instruction described questionnaire content, filing, and concept explanation. The basic information included personal information (i.e., sex, age,

TABLE 1 | Participant characteristics.

Variable		*N*	%
Gender	Male	195	52.00%
	Female	180	48.00%
	Total	375	100%
Age	19 and under	75	20.00%
	20–29	101	26.93%
	30–39	111	29.60%
	40–49	53	14.13%
	Above 50	35	9.33%
	Total	375	100%
Education	Junior middle school or below	5	1.33%
	High school	98	26.13%
	College/University	205	54.61%
	Master or above	57	15.20%
	Total	375	100%
Occupation	Student	149	39.73%
	Government official	74	19.73%
	Enterprise staff	116	30.93%
	Freelance/unemployment/ others	36	9.60%
	Total	375	100%
How often have you used social media?	Hardly ever	23	6.13%
	Occasionally	50	13.33%
	Daily	242	64.53%
	Several times daily	60	16.00%
	Total	375	100%
How often have you used health information social sharing?	Never	5	1.33%
	Hardly ever	64	17.07%
	Occasionally	183	48.80%
	Daily	115	30.67%
	Several times daily	8	2.13%
	Total	375	100%

education, and occupation) and the online activity information that consisted of social media use frequency, health information social sharing frequency, source, content type, and channel. The use survey of health information social sharing service was made up of 37 measurement items. The 5-point Likert format from 1 to 5 (1 = totally disagree, 5 = totally agree) was adopted in this study.

Before the formal distribution of the questionnaire, the questionnaire was reviewed and modified by a group of experts including professors, associate professors, and Ph.D. students in the field of information systems, user information behavior, human-computer interaction, and social media to ensure that the measurement constructs, indicators, and questions were set up in a scientific way. Finally, the scale was formed with eight variables and thirty measurement items (see **Table 2**).

The descriptive statistical analysis of all variables was shown in **Table 3**. The maximum and minimum of the variable reached 5 and 1, respectively, indicating that views of participants toward each item were mixed. The mean of most items can reach 3, which indicated the level of agreement of measurement items. More specifically, the variables EE, FC, MI, and BI have a higher mean, and considerable differences existed in PI and SN.

Data Analysis

This study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to simultaneously evaluate and analyze the structural model and the measurement model. The measurement model analysis and the structural model analysis were performed using SmartPLS 3.0.

RESULTS

Measurement Model Analysis

Reliability Analysis

Cronbach's alpha and composite reliability (CR) were used for reliability analysis. Cronbach's alpha was used to assess the extent to which observed variables explain the latent variables they describe, and CR was used to examine the degree of

TABLE 2 | Questionnaire survey items.

Latent variable	Item	Related documents
PE	PE 1: I think the social sharing tool allows me to share health information faster. PE 2: I think the social sharing tool improves my health information sharing efficiency. PE 3: I think the social sharing tool increases the possibility of finishing the sharing task. PE 4: I think the social sharing tool is helpful to my sharing behavior.	Venkatesh et al., 2003, 2012 Brown et al., 2016
EE	EE 1: It's easy for me to learn how to use social sharing tools. EE 2: I am clear about the use process of social sharing tools. EE 3: It's easy for me to be familiar with social sharing tools. EE 4: I think the social sharing tool is simple to handle.	Venkatesh et al., 2003, 2012; Chua et al., 2018
FC	FC 1: I have conditions to use social sharing tools (Wi-Fi, Mobile web, etc.). FC 2: I have skills to use social sharing tools (cognition, practices, etc.). FC 3: Social sharing tools are compatible with other software I use. (I can share information from online health community to my Wechat moments, micro-blogs, etc.) FC 4: When I have trouble using social sharing tools, consulting others might solve it.	Venkatesh et al., 2003, 2012; Wilson and Lankton, 2009
PI	PI 1: When I hear about a new technology/software/service, I usually want to try it PI 2: I'm always the one who uses new technology/software/services first, among my friends. PI 3:I'd like to try new technology/software/services.	Agarwal and Prasad, 1998; Sun and Jeyaraj, 2013 Gharaibeh et al., 2020
SN	SN 1: People who are important to me think that I should use social sharing tools. SN 2: People who are important to me would approve of my use of social sharing tools. SN 3: People who influence me think that I should use social sharing tools. SN 4: People whom I value his/her opinion think I should use social sharing tools.	Bagozzi and Dholakia, 2002; Wu et al., 2011 Joseph and Jacob, 2011
MI	MI 1:Some websites suggest people to use social sharing tools to share. MI 2:Some websites encourage people to use social sharing tools to share. MI 3:I find that some websites are using social sharing tools.	Venkatesh and Brown, 2001; Hong et al., 2008; Griffith et al., 2012
BI	BI 1: I will continue to use social sharing tools to share health information. BI 2: I will always use social sharing tools to share health information. BI 3: I will use social sharing tools frequently to share health information.	Venkatesh et al., 2003, 2012
SI	Imagine you are sharing health information to a group (moments, microblog, etc.) on some social sharing tool. Please evaluate: SI 1: The consistence between your self-identity and the image you project in the group. SI 2: You are an important member of the group. SI 3: You a valuable member of the group. SI 4: Your level of intimacy with the community SI 5: Your sense of belonging to the community	Chatzisarantis et al., 2009; Cheung and Lee, 2010; Shen et al., 2011

internal consistency of the corresponding items (Shi et al., 2021). Preliminary runs demonstrated high reliability of the questionnaire when Cronbach's alpha and composite reliabilities of each latent variable were all above 0.7 (Hou, 2004). The results of reliability are given in **Table 4**. The values of Cronbach's alpha were all above 0.85, and the values of CR were all above 0.9, thus, confirming the good reliability for the model.

Validity Analysis

It was generally accepted that in a model with good convergent validity, loadings should be larger than 0.7 and the latent values of average variance extracted (AVE) should be all above 0.5 (Hair et al., 2006). **Table 5** presents the analysis results on convergent validity, which indicates that the measurement model has good convergent validity.

The testing of discriminant validity was usually based on the standard proposed by Fornell and Larcker (1981). The square root of the AVE values of each latent variable are larger than the correlation coefficient (see **Table 6**). Furthermore, factor loadings and cross loadings were considered to test discriminant validity. Therefore, the questionnaire had good discriminant validity.

Structural Model Analysis

We confirmed the fit of the structural model, and the path model is calculated by the partial least square method. As shown in **Table 7**, the coefficient of determination R-square of mediators: EE and PE were 0.297896 and 0.389365, respectively. The R-square of the dependent variable behavioral intention was 0.607335. They were closed or larger than the standard value of 0.3, which indicated good model interpretation. Meanwhile,

TABLE 3 | Summary statistics.

Variable	Indicator	Minimum	Maximum	Mean	Std.	Standard deviation coefficient
PE	PE1	1	5	3.42	1.153	0.337
	PE2	1	5	3.37	1.144	0.339
	PE3	1	5	3.18	1.134	0.357
	PE4	1	5	3.49	1.067	0.306
PI	PI1	1	5	3.13	1.127	0.360
	PI2	1	5	2.93	1.140	0.389
	PI3	1	5	3.04	1.177	0.387
EE	EE1	1	5	3.56	1.083	0.304
	EE2	1	5	3.47	1.123	0.324
	EE3	1	5	3.61	1.052	0.291
	EE4	1	5	3.64	1.056	0.290
FC	FC1	1	5	3.75	1.098	0.293
	FC2	1	5	3.65	1.062	0.291
	FC3	1	5	3.66	1.044	0.285
	FC4	1	5	3.49	1.008	0.289
SN	SN1	1	5	3.18	1.065	0.335
	SN2	1	5	3.12	1.074	0.344
	SN3	1	5	3.10	1.069	0.345
	SN4	1	5	3.15	1.067	0.339
MI	MI1	1	5	3.49	1.079	0.309
	MI2	1	5	3.50	1.106	0.316
	MI3	1	5	3.64	1.065	0.293
SI	SI1	1	5	3.34	0.984	0.295
	SI2	1	5	3.05	1.043	0.342
	SI3	1	5	3.21	1.043	0.325
	SI4	1	5	3.20	0.982	0.307
	SI5	1	5	3.16	1.011	0.320
BI	BI1	1	5	3.57	0.997	0.279
	BI2	1	5	3.43	1.044	0.304
	BI3	1	5	3.42	1.059	0.310

TABLE 4 | Reliability analysis results.

Variable	Cronbach's α	CR
EE	0.93	0.95
FC	0.87	0.91
MI	0.87	0.92
PE	0.91	0.94
PI	0.87	0.92
SI	0.90	0.92
SN	0.94	0.96
BI	0.91	0.94

TABLE 5 | Convergent validity.

Variable	Factor loadings	AVE
EE	0.88–0.92	0.82
FC	0.76–0.89	0.72
MI	0.86–0.91	0.79
PE	0.86–0.92	0.79
PI	0.86–0.92	0.79
SI	0.75–0.88	0.71
SN	0.90–0.93	0.84
BI	0.91–0.92	0.84

based on the calculation of commonality and R^2, the value of goodness-of-fit (GoF) was 0.595 and larger than the standard value of 0.36, thus, confirming the good overall adaptation degree of the model. Then, we used the bootstrapping approach to estimate the path coefficients.

The final model output is shown in **Figure 3**, and the hypothesis validation results are shown in **Table 8**. As shown in **Figure 3** and **Table 8**, H2a, H3a, and H6 of the original hypothesis were not supported, while the rest of the hypotheses were supported.

TABLE 6 | Discriminant validity – the square root of average variance extracted (AVE)>latent variable correlation (LVC).

	BI	EE	FC	MI	PE	PI	SI	SN
BI	0.92							
EE	0.55	0.90						
FC	0.63	0.80	0.85					
MI	0.51	0.60	0.65	0.89				
PE	0.57	0.56	0.57	0.56	0.89			
PI	0.39	0.55	0.43	0.37	0.46	0.89		
SI	0.71	0.54	0.56	0.45	0.53	0.54	0.84	
SN	0.59	0.47	0.51	0.46	0.58	0.46	0.64	0.92

TABLE 7 | Communality and R^2 of the path model after adding mediation variables.

Variable	Communality	R^2
BI	0.84	0.61
EE	0.82	0.30
FC	0.72	
MI	0.79	
PE	0.79	0.39
PI	0.79	
SI	0.71	
SN	0.84	

DISCUSSION

The Influence of Attitude Beliefs on the Adoption of Health Information Social Sharing

The results of the study showed that PE had a positive impact on BI, which supports H1. Most people agree that social sharing services could simplify health sharing processes and increase heath sharing efficiency. Lots of health information are long, professional, and have great instant dissemination value, such as information about coronavirus disease 2019 (COVID-19) epidemic prevention. Thus, it is important for users to be able to share them effectively and easily. Whether health information social sharing fulfill user's expectation would affect their behavioral intentions.

The path coefficient of PI on BI was −0.103, the lowest of all factors, which showed that H2a was not supported. The higher the PI, the lower the BI would be. This is contradictory to the previous research conclusions. One possible explanation is that most of the survey samples of this study are "non-rookie," as well as experienced in using health information social sharing. The freshness of the service has faded for this type of users. Status Quo Bias Theory pointed out that people always prefer to keep their original state without making changes (Samuelson and Zeckhauser, 1988). Kim and Kankanhalli (2009) added more weight to the notion that the conservative users considered that the conversion cost was high when using sharing ways other than social sharing services. Thus, they were willing to conduct and adopt health information social sharing indeed.

Personal innovativeness had a significant positive impact on EE, which showed that H2b was supported. The more innovative a user is, the less he/she perceives the difficulty of health information social sharing, which corresponds to Roger's explanation toward users with different innovative characteristics.

The impact of attitude beliefs demonstrates that social sharing tools that can quickly share and disseminate real-time health information are more well-received. The design of social sharing tools should be easier to use on the basis of the user experience, correctly guide the user's operation, in the limited space and page information to easily find the share function, and simply and quickly achieve the aim (Xu and Tan, 2013). Moreover, humanized design is also essential. Zhang and Xiao (2017) note in their study that humanized social sharing services can improve mood and relieve stress. Moreover, the user's habits should be taken into account, and social sharing services should be carefully adjusted to avoid making changes that increase the difficulty of use.

The Influence of Control Beliefs on the Adoption of Health Information Social Sharing

This study reveals that the effect of EE on BI was not significant. The path coefficient was 0.018499, which was lower than expected, so H3a was not supported. It is opposing to the result of Tan et al. (2012) who confirmed that EE has a strong impact on BI because apps that require significant efforts to use would discourage consumers from adopting it. Descriptive statistics of effort expectation variables in this study showed that the mean of effort expectation was higher than that of other variables, and the mean of each item was above 3.5. This result indicates that health information social sharing is generally user-friendly at present, as well as learning to operate and use it is simple for most users. Thus, the impact of EE on BI is no longer significant. In reality, people can skillfully share and repost the trajectory of suspected cases and close contacts to the WeChat and QQ groups, which helps the epidemic information diffusion. The effect of EE on PE was positive, so H3b was supported. Social sharing promotes health information exchange on social media, which makes people feel empowered and informed as well as enables

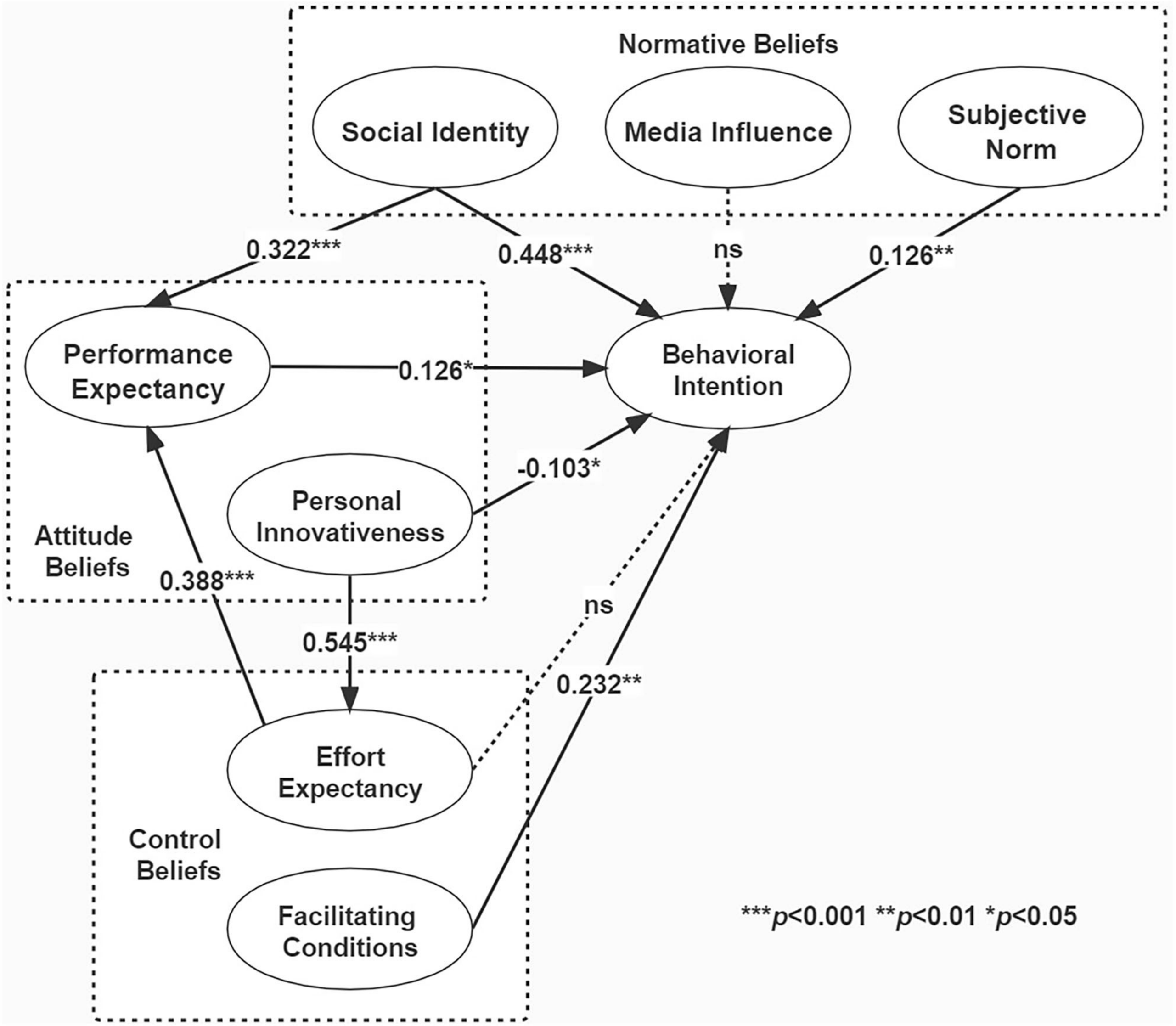

FIGURE 3 | The results of structural model path analysis. ***indicates significance at the 0.001 level; **indicates significance at the 0.01 level, and *indicates significance at the 0.05 level.

them to take an active role in their daily health management (Zhang et al., 2021).

FC had a significant positive impact on BI, so H4 was supported. People are more likely to adopt social sharing services while they obtain more usage support. In reality, with the evolution of the Internet age, people could share health information on their smartphones anytime and anywhere. Lots of wise information technology of med (WITMED) apps and online health communities are with good compatibility (Yin et al., 2020), so people are allowed to share their contents by using social sharing tools.

The impact of control beliefs demonstrates that only health information with good quality, content, and usability can improve user's adoption and further promote the sharing behavior. Social sharing services should optimize the interface design on the basis of users' needs and lower the usage threshold, so that more users can exchange and share health information on the interface with comfortable design, complete functions, and convenient operation.

The Influence of Normative Beliefs on the Adoption of Health Information Social Sharing

The result of this study shows that SN had a significant positive impact on BI, which showed that H5 was supported. The finding was consistent with Chong et al. (2012) and Taylor et al. (2011) of their past research studies, which suggested that SN plays a significant role in BI. The psychological principle in which SNs directly affect behavior intention was that as long as the

TABLE 8 | Path coefficients and hypothesis validation results.

Hypothesis	Path	Path coefficients	*T*-values	Significance	Hypothesis supported
H1	PE→ BI	0.13	2.03	*	Yes
H2a	PI→ BI	−0.10	2.20	*	No
H2b	PI→ EE	0.55	12.21	***	Yes
H3a	EE→ BI	0.02	0.23	Insignificant	No
H3b	EE→ PE	0.39	6.38	***	Yes
H4	FC→ BI	0.23	2.94	**	Yes
H5	SN→ BI	0.13	1.74	**	Yes
H6	MI→ BI	0.06	1.02	Insignificant	No
H7a	SI→ BI	0.45	6.33	***	Yes
H7b	SI→ PE	0.32	5.63	***	Yes

***$p < 0.001$; **$p < 0.01$; *$p < 0.5$.

actors thought the influencers expected their certain behavior, they would actively obey, even if they did not approve of this behavior or result. This can be concluded that the positive influence of family and friends can significantly increase the intention of health information social sharing. Kye et al. (2017) found that good subjective health was significantly associated with frequent information sharing, while family members were more likely to share health information. Especially, many older persons also have adult children living outside the home who could provide substantial support to the service if they could share useful healthcare knowledge to their parents and access specific, accurate information about their parents' health (Zulman et al., 2011).

This study reveals that the effect of MI on BI was not significant. The path coefficient was 0.056960, which was lower than expected, so H6 was not supported. In the descriptive statistics of variables, the mean of the three measurement items of MI was relatively high, which indicates that many users have obvious perceptions about the media direction of encouraging social sharing services. Xu et al. (2010) pointed out in their study that excessive promotion of mobile products in media has aroused users' mistrust, and the gap between usage experience and media promotion further strengthens users' prejudice against MI. One possible explanation is that people's suspicion of the media makes the adoption of health information social sharing not be positive publicity influenced.

Social identity had a significant positive impact on BI, so H7a was supported. Among all the constructs, SI has the highest ability to predict BI, indicating that the psychosocial factor was the most significant factor influencing the adoption of health information social sharing rather than the technological factor. Furthermore, SI had a significant positive impact on PE, so H7b was supported. This result shows that in essence, the intention of health information social sharing is to strengthen the connection with the "circle" and maintain the "image" of oneself in the circle more than to improve the efficiency of sharing. Therefore, factors that determine the adoption of SNA users are not only technical factors but more importantly whether the technology satisfies the social psychology behind the users. Zhang et al. (2017) believed that reputation, personal interests, and altruism would promote knowledge sharing in online health communities. For example, many online health communities design and implement an online reputation system as an incentive mechanism (Wang et al., 2020). The maintenance of reputation encourages people to pursue positive social identities in the hope of gaining other users' approval (e.g., likes, reposts, and comments) in order to enhance their self-esteem (Oh and Syn, 2015), a process that has the advantage of fulfilling social needs in an epidemic environment and effectively promoting the dissemination of health knowledge.

CONCLUSION

This study investigated the impact of beliefs on user's adoption intention of health information social sharing in online communities. Based on the UTAUT, combined with SIT and IDT, the hypothesized model of HISSA was proposed, and the relevant influencing factors of attitude beliefs, control beliefs, and normative beliefs were analyzed by using PLS-SEM, finally obtaining the following meaningful findings. The results show that PE (H1), FCs (H4), SNs (H5), and SI (H7a) were significant predictors of behavioral intention to use health information social sharing services. By using a questionnaire method, we found out that psychosocial factors of normative beliefs were the most critical factor influencing user adoption intention, and most of the hypothesized relationships were manifested. The results implied that the model of HISSA can help understand the influencing factors on user adoption behavior in a health context.

Theoretical and Practical Implications

The theoretical contribution of this study was to develop a new theoretical model in health information social sharing context by integrating both information technology and social psychology theory and investigates relationships between each independent variable and dependent variable (i.e., BI) in the model. This study then classified influencing factors on health information social sharing adoption into attitude beliefs, control beliefs, and normative beliefs. It enriches the theoretical structure of UTAUT and TPB and makes the research more persuasive and detailed. Additionally, the results examined good applicability and explanatory power of this model as well.

Based on the results, we argue that SI of normative beliefs is the most important predictor of user behavioral intention. The attention to psychosocial factors promotes this research process on healthcare information technology (such as mobile health apps and virtual health communities). In recent years, scholars have theorized that social psychology is critical in enabling the information sharing analytics process regarding healthcare IT because exploring the mechanism of health information social sharing is not independent from its context. For example, Lu et al. (2019) investigated what drives patients to share in online depression communities and found that a sense of shared identity, trust, and a sense of shared values had positive effects on their health information sharing behaviors. Jiang et al. (2020) argued that self-efficacy positively affected user sharing willingness in online health communities. Users' health information sharing was based on their interaction. The interaction effect between users was closely related to SI, communication, and understanding ability, judgment, and identification ability, which should be noticed to enhance self-efficacy. Despite these claims, evidence supporting the enabling importance degree of psychosocial factors has yet to be discussed in heath information sharing literature. Therefore, this article supports these claims and revealed that psychosocial factors are more significant than technological factors.

Furthermore, this study investigated the relationships between independent variables (i.e., PI-EE, EE-PE, and SI-PE) in the HISSA model that are scarcely mentioned in previous studies but important for a comprehensive understanding of the use of social sharing services. The results also have reference value for understanding the adoption, use, and sustainable use of information technology in the information sharing process and extend online knowledge sharing literature.

From the practical perspective, the results of this study are worthwhile not only for the researchers but also for those involved in the health information social sharing service and online health communities. Users are the principal part of online activities and play an important role in value co-creation through health information sharing. This study takes users as the research subject, helps understand their social sharing for health, and provides references for social sharing service providers. For example, since the SN and SI are two strong motivations for the user's behavioral intention, stakeholders of the social sharing service and virtual health communities can lean more on group or circle leaders to facilitate the dissemination of health information. Furthermore, owing to the development of big data and Internet technology over the years, the cost of health information seeking and sharing has been lowered significantly. Individuals have already realized the rapidness and convenience of health information social sharing services, so they are more likely to accept related apps and use them frequently. For this reason, this study helps people to improve their understanding of self-sharing behavior and raise the quality of health Information seeking, processing, and sharing. It provides the practical implication to improve people's health literacy and self-healthcare attention of the whole society.

Limitations

In this study, the hypothesis that PI has a positive impact on BI is not supported. In the following study, we will consider increasing the sample size and introducing the time dimension to further investigate the impact of PI on the adoption intention of health information social sharing at different stages of innovation diffusion.

Studies have pointed out that the prediction of adoption intention of UTAUT was different or even contradictory under different cultural backgrounds. The following study will collect sample data in the context of Western culture in order to conduct a comparative study on factors of cross-cultural health information social sharing adoption.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by School of Management, Shandong University. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

AUTHOR CONTRIBUTIONS

DS contributed to the conception and design of the study, reviewed, and edited the manuscript. RY analyzed and examined the data and wrote the original draft of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Will Natural Media Make Online Physicians More Trustworthy? The Effect of Media Naturalness on Patients' Intention to Use HIT

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Although previous studies have recognized the important role of patients' trust in promoting their intention to use health information technologies (HIT), most of those studies were under the "risk-benefit" theoretical framework. To deepen the understanding of patients' online consultation decisions, this paper develops a dual-path model investigating how patients develop trust beliefs toward online physicians from the perspective of communication. Drawing on media naturalness theory, we propose that HIT media naturalness will improve patients' perception of communication effort from online physicians and decrease communication ambiguity between patients and online physicians. This improved communication will further strengthen patients' trust in online physicians and promote their intention to use HIT. Based on a two-wave time-lagged survey from 361 participants, the empirical results demonstrated that the relationship between HIT media naturalness and patients' intention to use HIT is individually and serially mediated by two chains, including (1) perceived communication effort and patients' trust and (2) perceived communication ambiguity and patients' trust. We thus contribute to the related literature and provide practical implications.

Keywords: media naturalness theory, intention to use HIT, communication effort, communication ambiguity, trust toward online physicians

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INTRODUCTION

With the increasing attention to and demand for health information, online health care platforms have emerged as an important channel for individuals to obtain medical knowledge via the internet. The platforms provide patients with geographic convenience (Zhang and Zhang, 2021), online health consultation services (Wan et al., 2020), and good privacy protection (Zahedi et al., 2016). Although customers have recognized the advantages of online health care platforms, not all of them are willing to use these platforms. Thus, a large number of scholars have studied what would affect customers' intention to use health information technologies (HIT), which can be defined as the patients' willingness to receive health care services online, for example, through health care websites, remote consultations, virtual health communities, and so on (Slepchuk et al., 2021). Empirical evidence has shown that the characteristics of online health care platforms (i.e., Yang et al., 2018; Xie et al., 2020), patients' perception of HIT and online physicians (i.e., Le et al., 2019; Kokkoris and Kamleitner, 2020; Zhang and Zhang, 2021) and patients' attitudes (Li D. et al., 2020) affect patients' intention to use HIT.

According to the prior studies, trust toward online physicians has been demonstrated as an extremely important factor influencing patients' willingness to use HIT (Chen and Dibb, 2010; Li et al., 2018; Wan et al., 2020; Gong et al., 2021; Slepchuk et al., 2021; Yang et al., 2021). However, most of the extant studies revealing how patients develop trust beliefs were based on a risk-benefit framework (Fang et al., 2014; Kim, 2014; Ou et al., 2014; Sollner et al., 2016; Venkatesh et al., 2016; Yang et al., 2021). For example, Hong et al. (2019) showed that perceived risk was negatively related to patients' online trust; while perceived benefit was positively associated with patients' online trust. Little research has investigated how patients develop trust from other perspectives or theories. To deepen the understanding of patients' online healthcare continuance decisions, Zahedi et al. (2016) proposed a new design based on media naturalness theory (MNT) (Kock, 2004, 2009), pointing out the important role of media design features in influencing patients' trust and intention to use HIT in the digital context. Media's naturalness refers to the degree of similarity of the medium to the face-to-face communication, and MNT argues that high levels of media naturalness would reduce communication obstacles. Yang et al. (2021) also suggested that future studies could investigate the cognitive mechanism of customer behavior intention based on MNT. Responding to this call, this study aims to explore how characteristics of online healthcare platform, more precisely, media naturalness would affect patients' trust and their further intention to use HIT.

To investigate the mechanism on how media naturalness would influence patients' trust in online physicians and intention to use HIT, we draw on MNT and aim to reveal the internal mechanism from the perspective of communication. This is because media naturalness has been commonly shown to influence actors' perceptions and behaviors through the effectiveness of communication (Kock, 2002, 2005; Kock et al., 2015). Specifically, natural mediums are more likely to provide an immersive environment for patients to communicate with online physicians, which will make it possible for them to convey more detailed and accurate information (Kock, 2002; Zahedi et al., 2016). As a result, on the one hand, patients will be engaged in more communication interactions and perceive online physicians' communication effort; on the other hand, more information and perceived transparency in interaction (Zhang and Zhang, 2021) could help reduce communication ambiguity.

We believe that patients' perceptions of online physicians' communication effort and reduced communication ambiguity will further promote patients' trust in online physicians and enhance their intention to use HIT. This effect occurs because as patients can more readily perceive online physicians' communication effort, they are more likely to believe in the quality of health care information, and therefore trust, online physicians (Yoo et al., 2020). This trust, in turn, improves patients' intention to use HIT. Meanwhile, if less communication ambiguity is perceived in online health care platforms, patients will be more likely to receive and understand health information from online physicians (Zahedi et al., 2016); thus, they will be more likely to trust online physicians and more likely to use HIT.

In conclusion, drawing on MNT, our study provides a dual-path model regarding how media naturalness will influence patients' intention to use HIT from the perspective of communication. The theoretical model is shown in **Figure 1**.

This study offers three key contributions to the literature. First, drawing on MNT, we contribute to the research on patients' intention to use HIT. Existing studies have commonly investigated what would affect patients' behavioral intention from a risk-benefit framework. Responding to the call to explore more cognitive mechanisms (i.e., Yang et al., 2021), this study applies MNT and investigates how HIT media naturalness would influence patients' behavioral intention from the perspective of communication. To our knowledge, this study is the first attempt to develop the association between MNT and the intention to use HIT, which enriches related research fields. Second, although the previous studies have revealed that the characteristics of online platforms play important roles in affecting patients' intention to use HIT (i.e., Yoo et al., 2020; Gong et al., 2021), many more characteristics are worth exploring. By exploring how media naturalness would influence patients' intention to use HIT through a dual-path model, we aim to enrich studies on the antecedents of patients' behavioral intention. Last, by examining how perceived communication effort and communication ambiguity would affect patients' trust toward online physicians, our study also aims to expand the research of patients' trust.

THEORETICAL REVIEW AND RESEARCH HYPOTHESES

HIT Media Naturalness and Intention to Use HIT

In a broad sense, HIT is an approach that utilizes cloud-based database tactics to maintain patient related records, information, and reports, so as to properly and effectively handle cases (Singh et al., 2020). In a narrow sense, HIT is the way for patients to receive health services by using healthcare websites, remote consultations, online medical consultation, and virtual health communities (Ni et al., 2020; Slepchuk et al., 2021). Since behavioral intention refers to a person's willingness to perform certain behaviors (Glanz et al., 2015), in this study, we adopted the narrow sense of HIT and define the intention to use HIT as a person's willingness to receive health services online through remote consultations, virtual health communities, health apps or websites, and so on.

Characteristics of the platform have been shown to influence patients' intention to use HIT. For example, the blockchain certificate and structure guarantee provided by the platform would promote users' willingness to use (Xie et al., 2020; Yoo et al., 2020; Shao et al., 2022). These institutional cues can help individuals assess the ability and credibility of the platform, especially for those unfamiliar with it (McKnight et al., 2002; Kim and Lee, 2009). Meanwhile, the previous studies have shown that platform reputation has a significant influence on users' perceived information privacy concerns and their behavioral intention (Eastlick et al., 2006; Gong et al., 2021). Team strength

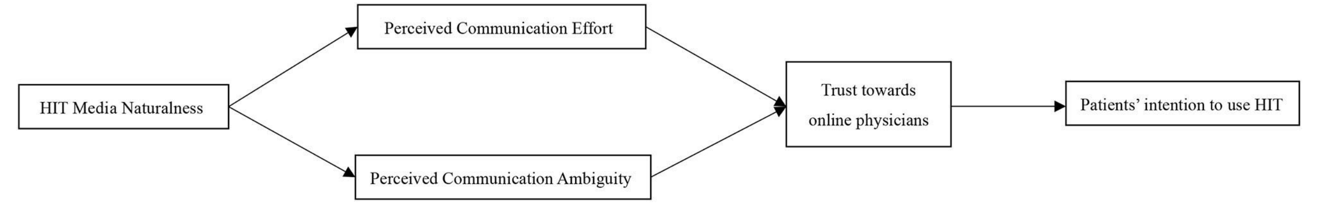

FIGURE 1 | Theoretical framework.

and similarity also have a positive influence on physician trust (Li D. et al., 2020). In addition, Yoo et al. (2020) proposed that when accessing the platform, patients often expect to find a better channel, the functions of which contribute to health information search, doctor selection, health consultation, and rating. As an important characteristic of online platform, media naturalness might be a potential factor influencing patients' intention to use HIT.

Based on the modern human evolution theory, Kock (2002) developed the media naturalness theory. Media naturalness is defined as the degree of similarity of the medium to the face-to-face communication (Kock, 2004). The extent of naturalness can be determined by five factors, including collocation, synchronicity, facial expressions, body language and speech (Kock, 2004, 2005). The higher the extent to which these factors are achieved, the more natural the people will perceive the HIT media to be. For example, people consider e-mail to be more unnatural and less preferable than face-to-face communication (Kock, 2001, 2002). This is because communication media suppresses some key elements in face-to-face communication as the internet is a media of low naturalness (Kock, 2007). The recent technologies have enabled Internet-based medium to provide sufficient information, making it much more similar to natural face-to-face communication than before. This kind of simulated face-to-face medium satisfies the needs of information transmission (Lim and Wollscheid, 2020). With the development of technology, the medium is likely to become increasingly natural.

We propose that the media naturalness of HIT will influence patients' intention to use HIT. First, by showing a high degree of collocation, HIT media naturalness provides an immersive environment for patients (Blau et al.'s, 2017). This will further act as a channel to communicate with online physicians and other patients in communities freely and anonymously. This immersive environment may protect patients' privacy and make them feel comfortable through online communication (Zahedi et al., 2016), thus increasing their intention to use HIT. It is therefore a reasonable expectation that the immersive environment created by the media naturalness of HIT promotes patients' intention to use HIT.

Second, enabling high levels of synchronicity and two-way communication of facial expression and body language, the HIT medium possesses a high level of social presence and promotes patients' intention to use HIT. Specifically, the previous studies have found that social context, online communication and interactivity would influence social presence in the context of virtual consultation (Tu, 2000). With high levels of media naturalness, HIT provides patients with two-way communication, which enables patients and physicians to respond to stimuli immediately and spontaneously (Blau et al.'s, 2017; Shkurko, 2022). Thus, patients will experience high levels of interactivity, which would increase their perceptions of social presence (Tu, 2001; Cui et al., 2013). Moreover, the social presence may elicit patients' emotions and make communication more expressive and engaging (Hwang and Park, 2007), which may thus enhance their intention to use HIT.

Third, the more natural the HIT medium is, the less communication uncertainty during communication, and patients' intention to use HIT will increase. Specifically, facial expression and body language can convey verbal and non-verbal information, which can reduce patients' perception of uncertainty about physicians and the technology (Shi et al., 2020). When patients feel less uncertainty, they are more likely to believe that they will receive accurate, comprehensive and high-quality diagnosis services through this natural communication (Shi et al., 2020). Patients' intention to use HIT may be enhanced under these circumstances. It is reasonable to propose that patients' intention to use HIT will be enhanced through HIT media which provides them with a more natural channel to communicate with others.

In short, HIT media naturalness may enhance patients' intention to use HIT by creating an immersive environment, increasing social presence and reducing uncertainty. Accordingly, we propose Hypothesis 1 as follows:

> **H1:** HIT media naturalness will be positively related to patients' intention to use HIT.

HIT Media Naturalness and Perceived Communication Effort/Communication Ambiguity of Online Physicians

We believe that HIT media naturalness will influence patients' perceived communication effort made by online physicians and their perceived communication ambiguity. Communication effort is one of the dimensions of physicians' benevolence, which refers to physicians' willingness to communicate with patients and make effort to improve their communication skills (Wan et al., 2020). The reduction of media naturalness usually leads to an increase in cognitive effort (Kock, 2002), which is related to patients' perceived physicians' communication effort. We propose that with higher levels of HIT media naturalness, patients are more likely to perceive online physicians' communication effort for the reasons discussed in the following paragraphs.

HIT media naturalness enables patients to clearly understand the information from online doctors in online health services. The high levels of media naturalness provide an immersive environment in which patients can interact with doctors effectively (Zahedi et al., 2016), which can help doctors better display and transmit their health information. In addition, when seeking for the health information, a natural medium always provide patients with doctors' information (such as the doctors' name, professional titles, etc.) (Wan et al., 2020). This information could help to reduce risk perception and uncertainty, improving patients' perception that the health services they receive are of high quality (Manchanda et al., 2015; Marrero et al., 2020). This will also act as a signal to show physicians' communication effort (Gong et al., 2021). When patients recognize that online physicians provide accurate information and reliable services, they would believe that doctors are making a greater effort to communicate.

In addition, HIT media naturalness enables patients to better recognize verbal and non-verbal messages from online physicians during online health services. With a higher level of naturalness, online communication is similar to the ability to interact and respond face-to-face, and patients would perceive the interaction to be more similar with real-world interactions (Klein, 2003). Natural HIT mediums provide virtual places for people to congregate and meet with other people's avatars, so as to create a feeling of being with others (Zahedi et al., 2016). In this case, the communication between doctors and patients becomes more natural, and hence doctors can express their concerns about patients through accurate speech and facial expressions (Kock, 2002). Meanwhile, the communication process with doctors enables patients to obtain enough information to effectively interpret the message being communicated, which is likely to contribute to an increase in perceived physicians' communication effort (Wu et al., 2020). In short, natural HIT enables patients to perceive more information and message from online physicians, so as to enhance their perception of online physicians' communication effort. Accordingly, we propose Hypothesis 2a as follows:

> **H2a:** HIT media naturalness will be positively related to patients' perceived online doctors' communication effort.

Communication ambiguity has commonly been defined as the degree of the mismatch between what is trying to be conveyed and what is actually comprehended in communication (Kock et al., 2015). Multiple interpretations will lead to the ambiguity of communication information (Nagasundaram and Wagner, 1992), For example, individuals raised in different cultural environments usually have different information processing schemas, which will lead individuals to interpret information in different ways (Kock, 2002, 2005). We argue that the communication ambiguity is more likely to arise in a low naturalness communication medium. The HIT media naturalness can reduce patients' perceived communication ambiguity in two ways.

On the one hand, a natural medium makes it possible to convey more speech and facial expressions to reduce mismatch, and consequently reduce communication ambiguity. Through online communication, dealing with ambiguity is more problematic because voice and gestures are missing (Hisarciklilar and Boujut, 2009). The improvement of media naturalness allows communication synchronicity and the ability to convey speech and facial expressions (Kock, 2002), which could help reduce communication ambiguity among actors. By contrast, a low natural medium, which represents a poor similarity of the medium with face-to-face communication (Blau et al.'s, 2017), is likely to increase the possibility of misunderstanding of communication clues, thus increasing communication ambiguity (Kock, 2002). Therefore, using a more natural medium for communication would help reduce communication ambiguity (Kock et al., 2015).

On the other hand, users' perception of transparency could help decrease the possibility of communication ambiguity through a natural medium. Through online communication, information asymmetry and information risk are greater due to the lack of face-to-face communication (Gong et al., 2021). With high levels of media naturalness, communication is more similar to face-to-face communication (Kock, 2004). Therefore, media naturalness enhances patients' perception of HIT transparency, which improves the physician–patient relationship and reduces communication ambiguity (Zhang and Zhang, 2021). In short, HIT media naturalness will decrease the possibility of patients' perceived communication ambiguity by conveying speech and facial expressions and enhancing patients' perceived HIT transparency. Accordingly, we propose Hypothesis H2b as follows:

> **H2b:** HIT media naturalness will be negatively related to patients' perceived communication ambiguity.

Communication Effort/Communication Ambiguity and Patients' Trust

Existing studies have commonly focused on patients' trust toward online health service from two dimensions: interpersonal and platform (Xie et al., 2020; Yoo et al., 2020; Gong et al., 2021). The interpersonal trust is mainly reflected in physician–patient interactions, which would be influenced by physicians' characteristics (e.g., benevolence, competence, integrity, etc.) (Li et al., 2018; Wan et al., 2020; Cantarutti and Pothos, 2021; Gong et al., 2021). Platform trust refers to patients' trust toward platform, which would be affected by blockchain certificates and structure guarantees provided by the platform (Xie et al., 2020; Yoo et al., 2020; Shao et al., 2022), platform reputation (Eastlick et al., 2006; Gong et al., 2021) and platform strength (Li D. et al., 2020). In this study, we focus on interpersonal trust from patients, which could be characterized by two dimensions, including cognition-based trust and affect-based trust (McAllister, 1995). The cognitive-based trust is called as "trust from the head" (Chua et al., 2008), which is related to a person's basic characteristics, such as ability and reliability (Dirks and Ferrin, 2002). The affective-based trust is called as "trust from the heart" (Chua et al., 2008), which is based on emotional bonds between members, such as understanding of reciprocal sentiments (McAllister, 1995; Dirks and Ferrin, 2002). Empirical studies have shown that physicians' abilities such as professional knowledge, physician rank, treatment effect and physician image are conducive to patients' cognitive trust, while physicians' integrity and benevolence are conducive to patients' affective-based trust (Wan et al., 2020).

We believe that the perceived high levels of online physicians' communication effort could help develop patients' trust toward online physicians. When patients perceive the high levels of physicians' communication effort, they will believe that the physician on the platform can provide sufficient and useful information, and would perceive the information to be of high quality and, in turn, derive more benefit from the platform (Yoo et al., 2020). Thereafter, patients will be more willing to believe that doctors can address their relevant health problems and will trust the physicians' diagnoses (Zahedi et al., 2016). In this case, communication effort of a physician are crucial in physician–patient communication, which increase patients' cognitive trust. In addition, when patients are aware of doctors' communication effort, it can promote smooth communication between physicians and patients and establish a good relationship between the two (Wan et al., 2020). When engaged in more emotional communication with online physicians, patients will develop more affective trust toward online physicians. In short, patients' perceived online physicians' communication effort will increase the possibility of patients' trust toward online physicians by enhancing their cognitive trust and affective trust. Accordingly, we propose Hypothesis H3a as follows:

> **H3a:** Patients' perceived online physicians' communication effort will be positively related to patients' trust toward online physicians.

We propose that patients' perceived communication ambiguity will also influence patients' trust toward online physicians. A perceived communication ambiguity is related to the degree of ambiguity, confusion, and lack of clarity involved in communication tasks (Kock et al., 2015). Communication is essential for building a mutually trusted physician–patient relationship (Bombeke et al., 2011). This is because medical and health services are based on information exchange (Rudawska and Krot, 2018), which requires a clear communication process between physicians and patients. The effectiveness of online medical care depends on the ability of physicians to deliver clear and understandable information (Zahedi et al., 2016). Vague or inaccurate communication often leads to misunderstanding, which may cause serious consequences (Hisarciklilar and Boujut, 2009). Failure to communicate or lack of communication may induce the deterioration of patients' physical disease (Kliszcz, 2000), resulting in their distrust of physicians (Cant, 2009). In short, the increase in communication ambiguity may damage patients' trust toward online physicians due to misunderstanding and misdiagnose. Accordingly, we propose Hypothesis H3b as follows:

> **H3b:** Patients' perceived communication ambiguity will be negatively related to patients' trust toward online physicians.

Trust and Intention to Use HIT

We argue that when trust their online physicians, patients are more likely to use HIT. First, if patients believe that online physicians are a credible source of information, which can provide reliable health information, they will be more likely to believe in the benefits of online health services (Yoo et al., 2020). Meanwhile, rational individuals would act in their own benefits when making the decision to trust (Berg et al., 1995; Lewicki and Bunker, 1995), thus affecting the continuance intention of using online health service (Hong et al., 2019; Yang et al., 2021). Second, trust plays an important role in the adoption of health services because it can eliminate the uncertainty related to the undesirable behavior of providers (Li et al., 2018). Trust toward online physicians will reduce patients' perceived uncertainty about the system and associated processes (Chen and Dibb, 2010), which can help them accept the risks, thereby promote the acceptance and use of HIT (Slepchuk et al., 2021). In short, patients' trust toward online services will promote their intention to use HIT by perceiving credible information and eliminating uncertainty. Accordingly, we propose Hypothesis 4 as follows:

> **H4:** Patients' trust toward online physicians will be positively related to their intention to use HIT.

The Chain Mediating Roles of Communication Effort/Ambiguity and Trust

As discussed here, it is predicted that HIT media naturalness can provide an immersive environment to create a sense of real-time interaction for patients. This interaction can stimulate more accurate communication, which can reduce the cognitive ambiguity in doctor–patient communication and enhance patients' perceived online physician's communication effort (Zahedi et al., 2016). When patients perceived high levels of online physician's communication effort, they would feel that doctors can provide useful information to solve relevant health problems. Then they would perceive greater information quality and benefits (Yoo et al., 2020), thus promoting their trust toward physicians and improving their intention to use HIT. According to the statements above, HIT media naturalness stimulates the cognitive process (perceived online physician's communication effort) of patients, then activates emotional units (trust), and finally affects their behavioral decision-making (intention to use HIT). Accordingly, we propose Hypothesis H5a as follows:

> **H5a:** Patients' perceived online physicians' communication effort and trust toward online physicians serially mediate the relationship between HIT media naturalness and patients' intention to use HIT.

According to the media naturalness theory, we also argue that the influence of HIT media naturalness on patients' intention to use HIT is serially mediated by patients' perceived communication ambiguity and trust. Specifically, high level of HIT media naturalness would provide a synchronous environment, which can help online physicians convey accurate speech and facial expressions (Kock, 2002). Then patients' perceived transparency is increased and the likelihood of misinterpretation of communication cues is reduced, thus reducing communication ambiguity. Furthermore, patients' needs for information exchange and satisfactory interpersonal communication can be met when they perceive less communication ambiguity from online physicians (Cant, 2009; Zahedi et al., 2016); thus, promoting mutual trust in the doctor–patient relationship. Furthermore, trust toward physicians can increase patients' recognition of the reliability and predictability of online health services (Cantarutti and Pothos, 2021), thus promoting patients' continuance intention of online health services. Accordingly, we propose Hypothesis H5b as follows:

> **H5b:** Patients' perceived communication ambiguity and trust toward online physicians serially mediate the relationship between HIT media naturalness and patients' intention to use HIT.

METHODS

Participants

A time-lagged survey was designed to test the hypotheses. We applied this time-lagged survey design to alleviate the potential common method bias due to our data collection from single source. According to the suggestions of Podsakoff et al. (2003) suggestion, creating a temporal separation by introducing a time lag between the measurement of independent variables and dependent variables is a way to remedy common method bias. Thus, we followed this suggestion and measured control variables, independent variable and mediators in the first stage at Time 1; and measured mediators in the second stage, as well as our dependent variable at Time 2. In addition, the time-lagged survey design has been shown to outperform the cross-sectional design because it can examine causation over time (Tims et al., 2016). By collecting the variables in sequence with a time lag, we can prove the causal effect between the independent variables and dependent variables.

We hired respondents and distributed questionnaires *via* Credamo, a reliable online Chinese data collection platform (www.credamo.com). The respondents were completely anonymous in the process of filling in the questionnaires and obtained certain material reward upon completion. We invited the respondents to participate in our time-lagged survey with a one-week interval. At Time 1 (T1), we hired 429 participants and asked them to rate all control variables (gender, age, education and pay level), HIT media naturalness, communication ambiguity, and communication effort. A week later, those who responded at T1 were asked to complete the Time 2 (T2) survey, which included items measuring trust and intention to use HIT, and we obtained 362 responses (response rate = 84.38%). After matching survey data from two time periods, we eventually obtained 362 responses. After sorting out an invalid questionnaire with missing information on age, 361 samples ($N = 361$) were finally included in our empirical analysis. As for gender, more than half the respondents (60.9%) were women and 91.7% of the participants were aged between 20 and 40 years. Regarding the education level, the proportion of undergraduates reached 71.7%. In terms of pay, 41.6% of the respondents' annual income was between 100,000 and 200,000 yuan in RMB.

According to Armstrong and Overton's (1977) suggestion, we tested non-response bias by comparing respondents with non-respondents in terms of control variables (e.g., in Chang, 2017; Ren et al., 2022). The results of t-statistics for the two groups showed no significant differences in age, pay and education level ($p > 0.05$), but a significant difference in gender ($p < 0.01$). To further examine whether this non-response bias from gender would influence our research results, we compared respondents with non-respondents in terms of independent variable (HIT medium naturalness) and mediators (communication ambiguity and communication effort). The results demonstrated that there were no significant differences ($p > 0.05$). The results in the regression section will also prove that gender will not be an impactful factor in regression, thus showing that non-response bias is not a serious issue in our study.

Measures

All measures used in this study have been validated in the previous research. Given that all administered items were in Chinese, translation and back-translation procedures were followed to ensure the quality of translations (Brislin, 1986). Each measure used a 5-point Likert-type scale ranging from "strongly disagree" to "strongly agree."

The HIT media naturalness (T1): Measures of media naturalness were developed based on Blau et al.'s (2017) definition of HIT media naturalness. In the work of Blau et al.'s (2017), they identified five criteria for assessing the level of media naturalness, including co-location, synchronicity, and the possibility of identifying and conveying facial expressions, body language, and natural speech. We thus developed a five-item scale accordingly (Cronbach-$\alpha = 0.828$). Instead of measuring the objective natural degree of one specific HIT, we measured respondents' perceived media naturalness based on their past HIT use experience. The respondents might have used different kinds of HITs, so they were able to give an average assessment for the HITs they have used, evaluating the average degree of similarity of those HITs to the face-to-face communication. This approach is consistent with our definition of media naturalness, which characterizes the degree of similarity of the medium to face-to-face communication.

An example item was "please recall your past experience of online health service, would you agree that the communication between you and your online physicians has high levels of synchronicity, which enabled immediate and spontaneous responses to stimuli?" The full questionnaire of HIT media naturalness we developed in this study is in the **Appendix**. The results suggested a satisfactory internal consistency reliability (CR) of items (which is equal to 0.830), and good validity (all factor loadings > 0.5; $\chi^2/df = 3.112$, RMSEA = 0.077, SRMR = 0.021, CFI = 0.991, IFI = 0.991).

Communication ambiguity (T1): For communication ambiguity, the three-item scale was adapted from Kock et al. (2015) and their measure (Cronbach-$\alpha = 0.826$). An example item was "please recall your past experience of online health consultation, would you agree that the communication between you and online physicians has often been ambiguous?."

TABLE 1 | Confirmatory factor analysis model fit results.

Models	χ^2	*df*	χ^2/df	RMSEA	SRMR	CFI	IFI
Five-factor model:							
The hypothesized five-factor model	548.599	283	1.939	0.051	0.049	0.931	0.932
Four-factor model:							
Combining HITMN and CA	852.459	293	2.909	0.073	0.057	0.855	0.856
Combining HITMN and CE	770.091	293	2.628	0.067	0.055	0.876	0.877
Combining HITMN and trust	897.125	293	3.062	0.076	0.061	0.843	0.844
Combining CA and CE	776.814	293	2.651	0.068	0.056	0.874	0.875
Three-factor model:							
Combining HITMN, CA, and CE	885.262	296	2.991	0.074	0.058	0.847	0.848
Combining CA, CE, and trust	932.386	296	3.150	0.077	0.063	0.835	0.836
Two-factor model:							
Combining HITMN, CA, CE, and trust	1,057.447	298	3.548	0.084	0.066	0.802	0.804
Combining HITMN, CE, trust, and BI	1,107.444	298	3.716	0.087	0.070	0.789	0.791
One-factor model:							
Combining all variables	1,234.092	299	4.127	0.093	0.073	0.757	0.758

HITMN, HIT media naturalness; CA, Communication ambiguity; CE, Communication effort; BI, Intention to use HIT.
χ^2, Chi-square; df, degrees of freedom; RMSEA, root mean square error of approximation; SRMR, standardized root mean square residual; CFI, comparative fit index; IFI, incremental fit index.

Communication effort (T1): Communication effort were measured with those of Wan et al. (2020) and their three-item scale (Cronbach-$\alpha = 0.757$). An example item was "please recall your past experience of online health consultation, would you agree that online physicians can understand your needs and interact with you effectively?"

Trust (T2): To assess patients' trust toward online physicians, we used the measure of Wan et al. (2020). The seven-item measure (Cronbach-$\alpha = 0.832$) has multi-item subscales corresponding to two dimensions: (1) Cognitive trust (three items; an example item is as follows: "I think online physicians will treat his/her work with professionalism and dedication"); (2) Affective trust (four items; an example item is as follows: "I think online physicians will treat me like a friend, and that we will be free to share our thoughts, feelings and hopes with each other").

Intention to use HIT (T2): An eight-item scale (Cronbach-$\alpha = 0.803$) was adapted from Li D. et al. (2020) and Slepchuk et al.'s (2021) measures. An example item was "If I am sick, I will choose an internet hospital for online inquiry."

Control variables (T1): In our statistical analysis, we controlled for gender, age, education level, and pay because these four variables are widely used demographic variables in management research and may be related to the study variables, including communication ambiguity, communication effort, trust, and behavioral intention.

RESULTS

Confirmatory Factor Analysis

We conducted confirmatory factor analysis *via* Amos 26 to assess the discriminant validity of the measurement model. The results in **Table 1** indicated that the hypothesized five-factor model fits the data well ($\chi^2/df = 1.939$, RMSEA = 0.051, SRMR = 0.049, CFI = 0.931, IFI = 0.932). The results provided support for taking the five constructs as distinctive variables, and the five-factor model was thus retained for substantial hypothesis tests.

Test of Common Method Bias

Due to that all data were collected from a single source, the potential impacts of common method bias should be examined. We followed the suggestions of Podsakoff et al. (2012) to test the potential common method bias. As shown in **Table 1**, the hypothesized five-factor model ($\chi^2/df = 1.939$, RMSEA = 0.0051, SRMR = 0.049, CFI = 0.931, IFI = 0.932) demonstrates better model fit indexes than the one-factor model ($\chi 2/df = 4.127$, RMSEA = 0.093, SRMR = 0.073, CFI = 0.757, IFI = 0.758). Moreover, no other alternative two-factor models, three-factor models, or four-factor models reveal better model fit. Thus, the common method bias issue was unlikely to have distorted the results of this study.

Hypothesis Test

Table 2 shows the descriptive statistics, correlations, and reliabilities of all the variables in our study. All internal reliabilities were above 0.80, except for communication effort. As expected, HIT media naturalness was significantly correlated with communication ambiguity ($r = -0.584$, $p < 0.01$), communication effort ($r = 0.629$, $p < 0.01$), trust ($r = 0.537$, $p < 0.01$) and behavioral intention ($r = 0.535$, $p < 0.01$). Communication ambiguity was significantly correlated with trust ($r = -0.602$, $p < 0.01$) and behavioral intention ($r = -0.401$, $p < 0.01$). Communication effort was significantly correlated with trust ($r = 0.605$, $p < 0.01$) and behavioral intention ($r = 0.543$, $p < 0.01$). Trust was significantly correlated with behavioral intention ($r = 0.610$, $p < 0.01$). These results provide preliminary support for our hypotheses.

We conducted path analysis with composites of research variables, using Amos 26 to examine our hypothesis. Item scores

TABLE 2 | Means, standard deviations, correlations, and reliabilities of studied variables.

	Mean	SD	1	2	3	4	5	6	7	8	9
1. Gender	1.609	0.489	_								
2. Age	3.422	0.204	−0.106*	_							
3. Education	3.931	0.595	0.031	−0.004	_						
4. Pay	2.080	0.905	−0.067	0.271**	0.258**	_					
5. HIT media naturalness	3.995	0.666	0.004	0.145**	0.071	0.330**	(0.828)				
6. Communication ambiguity	1.812	0.745	−0.106*	−0.092	−0.132*	−0.114*	−0.584**	(0.826)			
7. Communication effort	4.183	0.637	−0.017	0.136**	0.070	0.273**	0.629**	−0.650**	(0.757)		
8. Trust	4.271	0.471	0.037	0.154**	−0.042	0.160**	0.537**	−0.602**	0.605**	(0.832)	
9. Intention to use HIT	4.161	0.482	−0.034	0.110*	0.069	0.288**	0.535**	−0.401**	0.543**	0.610**	(0.803)

N = 361. $^{*}p < 0.05$, $^{**}p < 0.01$. Cronbach's alphas are shown in parentheses along the diagonal. SD, standard deviation.
Gender: 1 = male, 2 = female; Education level: 1 = primary school, 2 = middle school, 3 = junior college, 4 = undergraduate, 5 = master's degree or above; Pay: 1 = less than 100,000 yuan/year, 2 = 100,000–200,000 yuan/year, 3 = 200,000–300,000 yuan/year, 4 = 300,000–400,000 yuan/year, 4 = 400,000–500,000 yuan/year, 6 = more than 500,000 yuan/year; Age is in years.

TABLE 3 | Results of path analyses.

Path	Coefficient	SE	CR	95% CI intervals	
				Lower level	Upper level
HITMN→ BI	0.175***	0.035	5.022	0.086	0.276
HITMN→ CE	0.578***	0.041	13.97	0.458	0.693
HITMN→ CA	−0.683***	0.05	−13.788	−0.841	−0.52
CE→ Tr	0.257***	0.039	6.535	0.112	0.439
CA→ Tr	−0.241***	0.033	−7.304	−0.357	−0.109
Tr→ BI	0.482***	0.048	10.106	0.319	0.634
Gen→ CE	−0.018	0.054	−0.329	−0.119	0.079
Age→ CE	0.002	0.004	0.409	−0.006	0.01
Edu→ CE	0.012	0.045	0.267	−0.097	0.142
Pay→ CE	0.047	0.032	1.454	−0.013	0.111
Gen→ CA	−0.147*	0.064	−2.291	−0.287	−0.026
Age→ CA	−0.005	0.005	−1.079	−0.015	0.006
Edu→ CA	−0.149*	0.054	−2.738	−0.319	−0.008
Pay→ CA	0.101*	0.039	2.609	0.016	0.195
Gen→ Tr	0.014	0.038	0.379	−0.054	0.093
Age→ Tr	0.004	0.003	1.517	0	0.009
Edu→ Tr	−0.1**	0.032	−3.101	−0.174	−0.03
Pay→ Tr	0.022	0.022	0.982	−0.022	0.063
Gen→ BI	−0.05	0.039	−1.29	−0.134	0.028
Age→ BI	−0.004	0.003	−1.495	−0.013	0.004
Edu→ BI	0.03	0.033	0.917	−0.042	0.103
Pay→ BI	0.071***	0.023	3.036	0.03	0.116

HITMN, HIT media naturalness; CE, communication effort; CA, communication ambiguity; Tr, Patients' trust toward online doctors; BI, intention to use HIT. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

were calculated as the average for each variable. The path model included all direct paths from independent variable (HIT media naturalness) to mediating variables (communication ambiguity, communication effort, and trust toward online physicians), all direct paths from mediating variables to dependent variable (intention to use HIT), as well as the direct path from independent variable to dependent variable. Furthermore, indirect effects were tested *via* bootstrapping. After controlling for gender, age, education level and pay, the results of all paths were shown in **Table 3**. We also present the significant direct unstandardized path estimates in **Figure 2**.

As shown in **Table 3** and **Figure 2**, HIT media naturalness was positively related to patients' intention to use HIT ($\beta = 0.175$, $p < 0.001$). Thus, Hypothesis 1 was supported.

Hypothesis H2 proposed that HIT media naturalness will be positively related to patients' perceived online communication effort (Hypothesis H2a), and negatively related to communication ambiguity (Hypothesis H2b). As shown in **Figure 2**, there revealed a positive association between HIT media naturalness and patients' perceived online physician's communication effort ($\beta = 0.578$, $p < 0.001$), and a negative association between HIT media naturalness and communication ambiguity ($\beta = -0.683$, $p < 0.001$). Thus, Hypotheses H2a and H2b received the support.

The empirical results also showed that patients' perceived online physician's communication effort was positively related to patients' trust toward online physicians ($\beta = 0.257$, $p < 0.001$). And patients' perceived communication ambiguity was negatively related to patients' trust toward online physicians ($\beta = -0.241$, $p < 0.001$). Thus, Hypotheses H3a and H3b were supported.

Moreover, patients' trust toward online physicians was positively related to patients' intention to use HIT ($\beta = 0.482$, $p < 0.001$), which means that the higher the patients' trust toward online physicians, the higher is the patients' intention to use HIT. Thus, Hypothesis 4 was supported.

To test Hypothesis H5a and H5b, we tested the significance of the indirect effects *via* bootstrapping analysis by using Amos 26. The results of the indirect effects analyses were presented in **Table 4**.

As expected, patients' perceived online physicians' communication effort and trust toward online physicians significantly acted as serial mediators between HIT media naturalness and patients' intention to use HIT [indirect effect

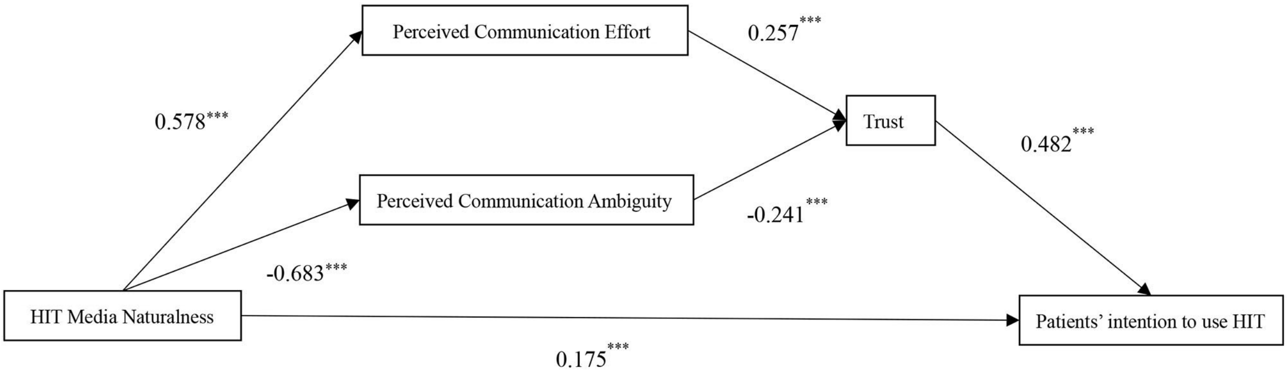

FIGURE 2 | Results of serially mediation model estimation. $N = 361$. $^{***}p < 0.001$. The path coefficient is unstandardized regression estimation.

TABLE 4 | Mediation effect estimated by bootstrap methods and 95% CI intervals.

Path	Estimates	95% CI intervals	
		Lower level	Upper level
Total indirect effect	0.151	0.09	0.223
Separate indirect effect			
Path 1: HITMN->CE->Tr->BI	0.072	0.031	0.137
Path 2: HITMN->CA->Tr->BI	0.079	0.033	0.141

HITMN, HIT media naturalness; CE, communication effort; CA, communication ambiguity; Tr, Patients' trust toward online doctors; BI, intention to use HIT.

$= 0.072$, $p < 0.001$, 95% CI intervals $= (0.031, 0.137)$], as its confidence interval did not include zero. Additionally, patients' perceived communication ambiguity and trust toward online physicians serially mediated the relationship between HIT media naturalness and patients' intention to use HIT significantly [indirect effect $= 0.079$, $p < 0.001$, 95% CI intervals $= (0.033, 0.141)$], as its confidence interval did not include zero. Thus, Hypothesis H5a and H5b received support.

DISCUSSION

Conclusions

Drawing on media naturalness theory, this study aims to test the potential mechanisms on the influence of HIT media naturalness on patients' intention to use HIT. Based on a time-lagged survey of 361 participants, the empirical findings revealed that HIT media naturalness was positively related to patients' intention to use HIT; the relationship between HIT media naturalness and patients' intention to use HIT was serially mediated through two paths, that is, (1) patients' perceived online physicians' communication effort and trust toward online physicians and (2) patients' perceived communication ambiguity and trust toward online physicians.

Theoretical Contribution

This study makes several theoretical contributions. First, by drawing on media naturalness theory, this study enriches the research on the intention to use HIT. The previous studies have demonstrated that the effectiveness of online healthcare platforms (Yang et al., 2018), patients' perceived fairness (Le et al., 2019), patients' prosocial motivation (Kokkoris and Kamleitner, 2020), patients' attitudes toward behavior (Li D. et al., 2020) and trust and interaction between the doctors and patients (Yang et al., 2021) play important roles in patients' intention to use HIT. Our study found that the HIT media naturalness promotes patients' intention to use HIT through two chain mediations. To our knowledge, this is the first attempt to explore how HIT media naturalness influences patients' intention to use HIT. This finding thus enriches the literature on patients' intention to use HIT by introducing media naturalness theory.

Second, this study expands the media naturalness theory to the field of HIT behavioral intention. Despite the rich development of media naturalness theory, there has not been adequate related research in the field of trust and intention to use HIT. Yang et al. (2021) suggested that future research could investigate cognitive mechanisms, such as exploring the influence of trust on online health based on media naturalness theory. Based on the extension of the media naturalness theory, Zahedi et al. (2016) first established an augmented virtual doctor office (AVDO), which simulates the naturalness of face-to-face visits through an immersive environment. In response to the call from those studies, we further extent the media naturalness theory to online healthcare research through empirical studies.

Third, this study contributes to the existing literature by enriching the antecedent of trust from the perspective of physician-patient communication. The previous studies have mainly focused on the patients' trust toward online physicians based on interpersonal relationships or doctors' characteristics. For example, online physicians' characteristics (such as benevolence, competence, integrity, etc.) would affect patients' trust in doctors (Li et al., 2018; Wan et al., 2020; Cantarutti and Pothos, 2021; Gong et al., 2021). Based on the media naturalness theory, our study investigates how media naturalness would affect the elements of physician–patient communication, then affecting patients' trust toward online physicians. Our empirical findings show that patients' perceived online physicians' communication effort and patients' perceived communication ambiguity affect their trust toward online physicians, which enriches the research of trust from the perspective of medium characteristics and communication process.

Practical Contribution

Our study also provides several practical contributions for HIT service. On the one hand, a more natural medium would promote patients' intention to use HIT. When accessing a platform, patients expect to find a useful channel, whose functions contribute to health information search, doctor selection, health consultation, and rating (Yoo et al., 2020). The empirical results of this study prove that media naturalness promotes patients' intention to use HIT. Therefore, a more natural medium can attract more users. In the process of establishing an online healthcare platform, designers could try to create more naturalness, which makes users feel like being with others (Zahedi et al., 2016).

On the other hand, adequate communication between doctors and patients is conducive to promoting patients' trust in online physicians, and improving patients' intention to use HIT. Patients often complain that physicians do not listen to their concerns, care about their problems, or provide enough information about their treatment (Hickson et al., 1994). Our study found that patients' perceived online physicians' communication effort promote their trust toward online physicians, while patients' perceived communication ambiguity reduces their trust toward online physicians. This suggests that in practical application, online physicians and platforms should actively take various measures to improve patients' trust, especially patient-centered communication skills.

Limitation and Future Direction

Although this study has provided both theoretical and practical contributions, there are also some limitations, which are worthy of further research and improvement. Specific research limitations and future research directions are discussed in the following paragraphs.

First, although this study discusses the influence of media naturalness on the intention to use HIT, we only apply the survey method to obtain data and test research hypotheses. However, the questionnaire method can only verify the correlation between research variables. To better test the possible causality in the hypothesis model, future research could use experimental methods for verification. For example, an experimental group and a control group could be established to study whether the experimental group would have higher intentions to use HIT when media naturalness is enhanced.

Second, the studied sample of this research may limit our understanding of users' intention to use HIT. Specifically, the majority of our participants (91.7%) are aged between 20 and 40 years. This is because although the patients are more likely to be lower aged or elder, the younger patients in targeted patient communication groups might be more willing to participate in the online survey (Li D. et al., 2020). Thus, failing to incorporate elderly users has always been a research gap in existing HIT-related studies (e.g., Hong et al., 2019; Li D. et al., 2020; Wan et al., 2020). The understanding and demand of HIT may vary considerably from elder users to young users. For example, studies have indicated that although elder people may show greater needs for healthcare services, they are less likely to use HIT (Slepchuk et al., 2021). This may be due to their physical disabilities, such as poor vision, cognitive disabilities, and motor skill limitations (Niehaves and Plattfaut, 2014), as well as their unwillingness to adopt HIT stemming from mistrust, high risk perceptions, and strong desire for privacy (Fox and Connolly, 2018). Therefore, failing to incorporate those elderly uses would make it difficult to generalize our research findings. We thus encourage future research to consider a wide range of people of different ages and experiences to verify and expand our research model.

Third, the HITs which respondents used in this study may prevent us from validating the research findings. Although we measured the respondents' perceived HIT media naturalness based on their past online healthcare experiences, which were not focusing on several kinds of HITs, our respondents commonly use some popular online health platforms in China (e.g., haodf.com, dingxiangyisheng.com, chunyuyisheng.com etc.). This might limit the validity of our research findings within specific HIT contexts. Thus, our findings should be viewed with caution when generalizing them to a broader context. In addition, as we focus on online health consultation in China, our conclusions may not be fully applicable to other cultures, because individuals raised in different cultural environments usually have different information processing schemas (Kock, 2002, 2005). It is necessary to test the validity of our conclusions in other cultures and modify our suggestions accordingly.

Fourth, given that self-reports were collected for all variables, this study did approach common method variance (CMV) influences with confirmatory factor analysis (CFA) procedure. Although it passed the homogeneity test eventually, potential CMV may still interfere with causality. Hence, the researchers can further enrich our results by obtaining measures from different sources in the future (Podsakoff et al., 2012). For example, the independent variable HIT media naturalness could be measured through survey, and the dependent variable patients' intention to use HIT could be obtained through objective data.

Finally, based on the media naturalness theory, our study investigated the mediating mechanism of media naturalness on the intention to use HIT. Future research could explore the boundary conditions of media naturalness. For example, patients with different personalities or ages may perceive different degrees of communication ambiguity even when faced the same level of media naturalness.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors contributed to the article and approved the submitted version.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX: MEASURES OF HIT MEDIA NATURALNESS

Please recall your past experience of online health service, would you agree that (1) the communication between you and your online physicians made you feel that you were co-located in the same physical space. (2) The communication between you and your online physicians had high levels of synchronicity, which enabled immediate and spontaneous responses to stimuli. (3) The interaction between you and your online physicians enabled you to identify and convey facial expressions. (4) The interaction between you and your online physicians enabled you to identify and convey body language. (5) The communication between you and your online physicians enabled you to convey natural speech.

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How Does Media Use Promote the Purchase of Private Medical Insurance? A Moderated Mediation Model

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Various information media (such as TV and the Internet) have become the main channels through which for people to obtain information. Previous studies showed that media use influences the purchase of private medical insurance; however, research on its internal influence mechanism is still relatively weak. Using data from the Chinese General Social Survey 2017, this study constructed a moderated mediation model to analyze the mechanism of the influence of media use on the purchase of private medical insurance. Individuals' self-rated health status was used as a mediator and individual cognitive ability was used as a moderator. The results showed that self-rated health status played a partial mediating role and individual cognitive ability played a negative moderating role in the direct path between media use and the purchase of private medical insurance. Furthermore, in the indirect path, individual cognitive ability negatively moderated the impact of media use on self-rated health status.

Keywords: media use, private medical insurance, self-rated health status, cognitive ability, moderated mediation model

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INTRODUCTION

With society entering the information development stage, the media has become an indispensable part of our lives. Especially during the COVID-19 pandemic, the Internet has become our primary channel of news and health knowledge, and more and more people choose online healthcare platforms for medical treatment. Moreover, studies showed that when people watch movies about health risks, they learn the importance of private medical insurance through some online film and television review platforms, which promote individuals to purchase private medical insurance (Gao et al., 2022). When people learn about health and risk through the media, it is worth noting whether this news about risk events and health can increase people's risk awareness and prompt them to take effective risk diversification measures (such as purchasing private medical insurance). In China, medical insurance includes social medical insurance schemes and private medical insurance. The social medical insurance schemes are funded by the government and aim to relieve the residents' financial burden caused by illness, but they cannot fully compensate for medical expenses and have certain restrictions (Ramesh et al., 2014). Private medical insurance requires people to pay their own premiums, but it can provide the insured with out-of-pocket compensation for medical expenses (the medical expenses that the insured still needs to bear after the reimbursement of social medical insurance). Private medical insurance is also one of the effective means of risk diversification and sharing, which can affect the application of the health security system (Yip et al., 2012). However, since the launch of private medical insurance in 1998, the market demand for private medical insurance in China has been relatively low (Liu et al., 2018). Therefore, the factors influencing demand for private medical insurance deserve attention.

Some studies found that consumers will purchase private insurance only after they meet the basic consumption needs of life, and the possibility of purchasing private insurance increases with the increase in individual or family income (Showers and Shotick, 1994; Ying et al., 2007; Corman et al., 2009). A series of empirical studies about health economics suggested that residents with better health status who do not smoke and are not overweight are more likely to purchase private medical insurance (Jerant et al., 2012; Buchmueller et al., 2013). Additionally, an individual's education level, employment status, employer type, and social medical insurance status have also been confirmed to affect the purchase of private medical insurance (Wan et al., 2020). Up to date, there hasn't been much research regarding the effect of media use on purchasing private medical insurance. Their findings are mainly as follows: more information about insurance can be obtained when people use the media (Lee, 2012), thus improving their insurance literacy and enhancing their understanding of insurance (Browne and Kim, 1993). On the other hand, insurance companies can cooperate with media companies to popularize their insurance products among consumers through big data analysis and achieve more efficient sales (Brown and Goolsbee, 2000).

Are there other influencing mechanisms? Some studies have found that media use can affect an individual's self-rated health status (Lohaus et al., 2005; Bundorf et al., 2006; Fenton and Panay, 2013). In the age of the low development level of the information media, people often seek advice about health from their friends or family who may also have a low level of health literacy (Loewenstein et al., 2013). Nowadays, the Internet can provide people with professional and comprehensive knowledge about health and healthcare online services. Those will help people develop healthy living habits and improve their health status. Furthermore, some studies found that their proactive behavior in seeking out health information may drive them to purchase private medical insurance (Furtado et al., 2016; Ndumbe-Eyoh and Mazzucco, 2016). However, to our knowledge, there is no study to explore the relationship between media use, health status, and private medical insurance. This study attempts to address these gaps by examining the mediating role of self-rated health status on the relationship between media use and the purchase of private medical insurance.

Additionally, studies revealed that people with varying cognitive abilities take different actions when given information about health and insurance (Lubinski, 2009; Fowler et al., 2017). In the process of using the media, individuals with different cognitive abilities judge the credibility of information differently when the media releases the same information (Lubinski, 2009). Previous studies suggested that Internet use has an impact on the health of the elderly, and the whole process is negatively moderated by individual cognitive ability (Wang et al., 2020). Therefore, both theoretically and empirically, it is necessary to explore whether individual cognitive ability plays a moderating role in the direct and indirect paths of the impact of media use on purchasing private medical insurance.

Overall, the core issue of this study included two aspects: (1) whether the mediating effect of self-rated health status was significant and (2) whether the moderating effect of cognitive ability was significant. Using data from the Chinese General Social Survey 2017, this study constructed a moderated mediation model to study the core issue. The results showed that self-rated health status played a mediating role between media use and the purchase of private medical insurance. Cognitive ability played a negative moderating role in both direct and indirect paths. This study enlarges the scope of the research of private medical insurance's demand to explicitly include both self-rated health status and cognitive ability simultaneously. The research may give practitioners an increased understanding of how media use affects the purchase of private medical insurance, which can then be used to help insurance companies and the government spread knowledge about insurance, especially in the emerging area of big data analysis. The theoretical contribution of this paper is to further enrich the analysis of the mechanism of the effect of media use on the purchase of private medical insurance.

The remaining sections of this paper are as follows: Section "Theoretical Background and Hypothesis Development" introduces the theoretical background and hypothesis development. Section "Data, Variables, and Methods" explains the variable sources and the estimation method. Section "Findings" reports the findings. In Section "Robustness Check," the robustness of the regression results is presented. Section "Discussion" presents a discussion. The final section is the conclusion of this paper.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Media Use and the Purchase of Private Medical Insurance

The theory of planned behavior (TPB) (AJZEN, 1991) and the health-belief model (HBM) (Rosenstock et al., 1988) have become theoretical frameworks for the analysis of health-related behavior (McEachan et al., 2011; Huang et al., 2020), and have been supported by some empirical research in the field of consumer behavior (Amaro and Duarte, 2015). The TPB held that individuals' behavior is decided by their intentions, which is mainly influenced by their attitude toward the behavior, subjective norm, and perceived behavioral control (AJZEN, 1991). The HBM emphasized the effect of individual health beliefs on future preventive behavior (Rosenstock et al., 1988). Both theories use individual-level approaches to predict health and risk transfer behaviors (Gerend and Shepherd, 2012), and these decisions are made by individuals in a deliberative process. Moreover, in the traditional theory of insurance demand, economists believed that consumers purchase insurance to transfer uncertain risks and receive corresponding economic compensation when risk events occur (Knight and Hyneman, 1921). Arrow (1963) proposed that risk avoiders are more willing to purchase insurance than risk seekers in the medical-care market based on three assumptions: that consumers are completely rational; the insurance market is a perfectly competitive market; and insurance payouts can fully cover economic losses. Since these three assumptions are obviously different from the actual market, the traditional theory of insurance demand has obvious limitations. With the development of behavioral economics, the modern theory of insurance demand proposed a decision-process on risk and policy analysis (Kunreuther et al., 1984). Based on the TPB, HBM, and modern insurance demand theory, we can infer that an individual could first identify the nature of risk associated with health and safety by collecting a large amount of information, then assess the potential loss caused by such risk, and finally decide to purchase insurance. If the level of information media development is low, the whole process of searching for information needs to consume a lot of time and economic cost. However, nowadays, information media (such as the Internet and TV) are highly developed, which helps consumers obtain risk-related information more conveniently than before and provides a more effective way for insurance companies to spread risk and insurance knowledge.

According to some studies, media use can positively affect the purchase of private medical insurance (Browne and Kim, 1993; Brown and Goolsbee, 2000; Manski, 2000; Beiseitov et al., 2004; Liu et al., 2014; Karaca-Mandic et al., 2017). First, from the perspective of insurance companies, the development of information media can increase the exposure of insurance companies' advertising, thus promoting the purchase of private medical insurance to consumers (Brown and Goolsbee, 2000). In particular, the development of the Internet can help insurance companies utilize diversified advertising platforms and optimize the service process. From the perspective of consumers, they can purchase medical insurance online due to the development of Internet technology, which brings great convenience to consumers (Li and Shiu, 2012). Some empirical studies showed that media use can drive consumers to purchase private medical insurance by improving an individual's trust in society and interaction frequency with others (Manski, 2000; Beiseitov et al., 2004; Liu et al., 2014). The influence of social trust and social interaction on the purchase of private medical insurance is mainly reflected in endogenous interaction, which can enhance the prevalence of financial behavior in the group (Manski, 2000). Moreover, media use can also improve an individual's financial literacy, which can increase the possibility of purchasing private medical insurance (Pahlevan Sharif et al., 2020). Therefore, the first hypothesis is proposed in this study.

> ***Hypothesis 1.*** *Media use has a significant positive impact on the purchase of private medical insurance.*

Self-Rated Health Status as a Mediator

The HBM believed that when individuals learn health and risk information, they will make expected utility judgments about unhealthy and risky behaviors (Rosenstock et al., 1988). When they develop a belief that a serious health problem or risky behavior makes them vulnerable, they could follow a particular health recommendation to reduce the consequences of that risk (Rosenstock et al., 1988; Gerend and Shepherd, 2012). Lots of researchers suggested that individuals who use the media to learn about risk and health insurance are often more concerned about their health status (Lambert and Loiselle, 2007; Atkinson et al., 2009). A key focus of this study, which is often overlooked, is that the relationship between media use and the purchase of private medical insurance may be mediated by the self-rated health status of individuals. Individuals use the media to obtain health-related information, including physical and mental health information, to judge their own health status and take actions to improve their health (Bundorf et al., 2006). Some studies on psychology suggested that the use of social media can relieve the psychological pain of some patients (Fenton and Panay, 2013; Ndumbe-Eyoh and Mazzucco, 2016). They can see the positive treatment results shared by doctors and other patients on social media (Zhang et al., 2020), which can relieve the psychological pressure of patients. It has also been discovered that young adolescents who use various types of media to obtain health information can ease their self-perceived pressure (Lohaus et al., 2005).

Furthermore, many empirical researches indicated that self-rated health status has a casual impact on the purchase of private medical insurance (Shmueli, 2001; Love and Smith, 2010; Atella et al., 2012). Individuals with a poor self-rated health status will incur more expected medical expenses, and they are more likely to purchase medical insurance. However, from the perspective of insurance companies, in order to prevent the problem of adverse selection, they often need a health assessment of the insured. As a result, individuals in poor health status will be rejected from purchasing private medical insurance, while individuals in better health status are likely to be insured by private medical insurance (Atella et al., 2012). Additionally, researchers found individuals who have a better self-rated health status are less likely to take risky actions, suggesting they tend to be risk averse and more likely to purchase private medical insurance (Doiron et al., 2008). In sum, this study predicted the second hypothesis that media use may drive individuals to purchase private medical insurance by affecting their self-rated health status.

> ***Hypothesis 2.*** *Self-rated health status plays a mediating role between media use and the purchase of private medical insurance.*

Individual Cognitive Ability as a Moderator

Based on the TPB theory and the theory of reasoned action (TRA), cognitive self-regulation plays an important role in the whole process, from the generation of belief and motivation to some behaviors (Ajzen, 2015; Tomczyk et al., 2020). People with different cognitive abilities process information differently, hold different attitudes toward certain things, and finally take different actions. Social-cognitive theory suggested that individuals are likely to be misled by false information when they use the media, especially on the Internet, where anyone can post information. It is the key to identifying false information that individuals have better cognitive ability. Individuals' cognitive ability was classified in terms of their ability to apprehend experience, educe relations, and correlates (Spearman, 1927). Previous studies concluded that, even under ideal conditions, the initial effects of false information cannot be simply eliminated by pointing out that it is incorrect, particularly for individuals with relatively weak cognitive ability (De keersmaecker and Roets, 2017). On the contrary, strong cognitive ability and good cognitive literacy enable individuals to better understand the true meaning of information so as to take corrective actions (Maitra, 2010).

In terms of health behavior, individuals with weak cognitive ability may overestimate their health status when they get some false information about health assessment (Lubinski, 2009; Fowler et al., 2017), and they continue to carry out some unhealthy life behaviors and do not take further measures to improve their health. Prior studies found the relationship between Internet use and health status of the elderly is negatively moderated by individual cognitive ability (Wang et al., 2020, 2021). Furthermore, based on financial behavioral theory, individuals need to browse news and obtain information to make financial decisions, which is usually the most beneficial to themselves (Lind et al., 2020; Pahlevan Sharif et al., 2020). However, the expected effect will not be achieved if they cannot make a reasonable judgment about the accuracy of the information. In addition, many insurance companies may exaggerate when selling in order to improve their sales performance. At this time, people with strong cognitive ability can understand the terms of insurance products well and will not purchase insurance. Therefore, individual cognitive ability is likely to negatively moderate the relationship between media use and the purchase of private medical insurance. This study proposed the third hypothesis and the fourth hypothesis, and drew the conceptual framework shown in **Figure 1**.

> ***Hypothesis 3.*** *Individual cognitive ability plays a negative moderating role in the direct path of media use on purchasing private medical insurance.*

> ***Hypothesis 4.*** *Individual cognitive ability plays a negative moderating role in the indirect path of media use on purchasing private medical insurance.*

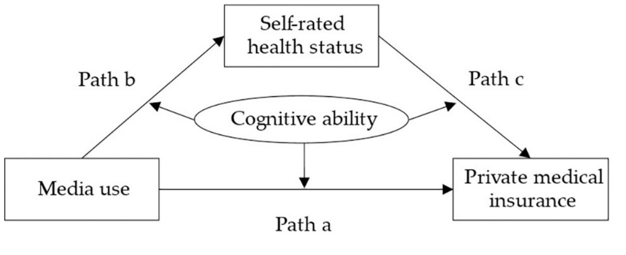

FIGURE 1 | Conceptual framework.

DATA, VARIABLES, AND METHODS

Sample and Data Collection

The data were extracted from the Chinese General Social Survey 2017 (CGSS2017). The CGSS is the earliest continuous and comprehensive academic survey project in China. The first CGSS was launched by the Renmin University of China and the Hong Kong University of Science and Technology in 2003. The CGSS aims to systematically monitor the changing relationship between social structure and quality of life in China (Bian and Li, 2014). The CGSS2017 employed a stratified multi-stage probability proportional to size (PPS) sampling design and it consisted of three modules, namely, the core module, social network module, and family questionnaire module. These data contain essential information on the frequencies of media use, indicators of self-rated health and cognitive ability, and whether respondents purchased private medical insurance. The final analysis sample included 12,032 respondents with non-missing values in the variables of interest.

Variables

The dependent variable, independent variable, mediator, moderator, and control variables used in this study are shown in **Table 1**.

Dependent Variable

The dependent variable was measured using the question: "Do you have purchased private medical insurance?" The choice of "Yes" was coded as 1 and "No" was coded as 0.

Independent Variable

The core explanatory variable of this study is the frequency of media use of respondents, which included traditional media use and new media use (Hu and Li, 2019). Traditional media consisted of four items: newspapers, magazines, radio, and television. The respondents were asked how often they used these four kinds of media in the past year. The responses of each item were measured using a five-point Likert scale: "1 = never," "2 = rarely," "3 = sometimes," "4 = often," "5 = very frequent." In this study, we used the average value of the four questions' answers to constitute traditional media use, which was a continuous variable. New media use was measured using Internet and mobile customization messages. The respondents were asked to indicate how often they used those two media in the past year. The responses and coding were the same as the items of the traditional media use scale.

Mediator

Self-rated health as a mediator was measured using the respondents' self-rated physical health and self-rated mental health (Wang and Geng, 2019). Regarding self-rated physical health, the respondents were asked, "How do you feel about your current physical health?" The responses were measured using a five-point Likert scale: "1 = very unhealthy," "2 = relatively unhealthy," "3 = average," "4 = relatively healthy," "5 = very healthy." Regarding self-rated mental health, the respondents were asked, "In the past 4 weeks, how often did you feel

TABLE 1 | Variable definitions and descriptive statistics ($N = 12{,}032$).

Variable	Variable definition	Mean	Std. Dev.
Dependent variable			
Insurance	1 if the respondent has purchased private medical insurance, 0 if otherwise	0.12	0.32
Independent variables			
Traditional media use	From 1 to 5, the frequency of the respondent’s use of traditional media goes up	2.23	0.71
New media use	From 1 to 5, the frequency of the respondent’s use of new media goes up	2.25	1.24
Mediator			
SRH	From 1 to 5, the self-rated health status of the respondent gets better	3.63	0.88
Moderator			
Cog	From 1 to 5, the cognitive ability of the respondent gets stronger	2.45	0.78
Control variables			
Age	The age of the respondent	51.09	16.70
Age^2	The square of the age	2889	1729
Gender	1 if the respondent is female, 0 if the respondent is male	0.53	0.50
Education	Education level of the respondent: “1 = junior college and below,” “2 = undergraduate,” and “3 = graduate and above”	5.16	3.27
Marital status	1 if the respondent is married, 0 if the respondent is unmarried	0.78	0.42
Family economic status	From 1 to 5, the family economic status of the respondent gets better	2.55	0.75
Social medical insurance	1 if the respondent has participated in social medical insurance, 0 if otherwise	0.92	0.27
Social endowment insurance	1 if the respondent has participated in social endowment insurance, 0 if otherwise	0.72	0.45

depressed?” The responses were similarly measured using a five-point Likert scale: “1 = always,” “2 = often,” “3 = sometimes,” “4 = seldom,” “5 = never.” In this study, we took the average value of the sum of the self-rated physical and mental health status as a mediator, ranging from “1” to “5,” where the higher the value was, the better the respondents self-rated their health status.

Moderator

The moderator was individual cognitive ability. There is a clear agreement that cognitive ability is supported by mathematical, spatial, and verbal abilities (Lubinski, 2009). Furthermore, verbal ability plays an extremely important role in individual cognitive ability. There are four questions in the CGSS2017 that represent an individual’s cognitive ability (Wang et al., 2020): (a) “What do you think of your ability to listen to Mandarin?,” (b) “What do you think of your ability to speak Mandarin?,” (c) “What do you think of your English listening ability?,” (d) “What do you think of your English speaking ability?” The responses were measured using a five-point Likert scale: “1 = cannot speak at all,” “2 = relatively poor,” “3 = average,” “4 = relatively good,” “5 = very good.” This study obtained the moderator by adding the answers to these four questions together and then multiplying them by 0.25, and a higher value meant better individual cognitive ability.

Control Variables

Based on the previous literature review, the control variables selected in this study included age, the square of age, gender, education level, marital status, social health insurance, and social endowment insurance (Showers and Shotick, 1994; Ying et al., 2007; Corman et al., 2009; Lee, 2012; Buchmueller et al., 2013). **Table 1** shows the definitions and assignments of these control variables. The impact of family income on the purchase of private insurance is greater than that of personal income (Corman et al., 2009); therefore, this study adopted family economic status as a control variable. Family economic status was coded as a five-item scale: “1 = well below average,” “2 = below average,” “3 = average,” “4 = above average,” “5 = well above average.” In addition, social insurance also has an impact on the purchase of private medical insurance (Ying et al., 2007); therefore, this study took social medical insurance and social endowment insurance as control variables.

Methods

To analyze the mechanism of the influence of media use on the purchase of private medical insurance, the moderated mediation model was selected. We constructed Equations (1)–(3) based on the mediating effect model (Baron and Kenny, 1986), moderating effect model (Baron and Kenny, 1986), and moderated mediation model (Muller et al., 2005), respectively. Among the three equations, $Insurance_i$ is the dependent variable, $Media_i$ is the independent variable, SRH_i is the mediator, Cog_i is the moderator, and X_i represents all variables that affect private medical insurance. $Media_i$, SRH_i, and Cog_i are all variables that were mean-centered because the process of mean-centering can reduce the problem of multicollinearity in regression equations and better explain the interpretation (Sinacore, 1991; Dawson, 2013). The interaction term between media use and cognitive ability is the product of media use and cognitive ability. The interaction term between self-rated health status and cognitive ability is the product of self-rated health status and cognitive ability. In addition, the mean-centering did not make any difference to the testing of the interaction term; the p-value for the interaction term and the subsequent interaction plot should be identical (Kromrey and Foster-Johonson, 1999; Dalal and Zickar, 2011). $Control_{ij}$ indicates the control variables, including age, age^2, gender, education, marital status, family economic status, social medical insurance, and social endowment insurance. α, β, and γ values are coefficients to be determined, while ε_i, μ_i, and ϵ_i are error terms.

$$
\begin{aligned}
&Pr(Insurance_i = 1|X_i)\\
&\quad = \Phi(\alpha_0 + \alpha_1 Media_i + \alpha_2 Cog_i + \alpha_3 Media_i * Cog_i\\
&\qquad + \sum \alpha_j Control_{ij} + \varepsilon_i)
\end{aligned}
\tag{1}
$$

$$SRH_i = \beta_0 + \beta_1 Media_i + \beta_2 Cog_i + \beta_3 Media_i * Cog_i + \sum \beta_j Control_{ij} + \mu_i \quad (2)$$

$$Pr(Insurance_i = 1|X_i) = \Phi\left(\gamma_0 + \gamma_1 Media_i + \gamma_2 Cog_i + \gamma_3 Media_i * Cog_i + \gamma_4 SRH_i + \gamma_5 SRH_i * Cog_i + \sum \gamma_j Control_{ij} + \epsilon_i\right) \quad (3)$$

Since the dependent variable is binary, Equations (1) and (3) used the probit model. When analyzing the mediating and moderating effects, the coefficient significance test of the probit model is the same as that of the OLS, but the coefficients cannot be directly used to calculate the effect size (Iacobucci, 2012). SRH_i is a continuous variable; therefore, Equation (2) adopted the OLS model. If the coefficient α_1 is significant (H_0: $\alpha_1 = 0$ is rejected), we conclude that media use significantly affects the purchase of private medical insurance. At the same time, if the coefficient α_3 is significant (H_0: $\alpha_3 = 0$ is rejected), we conclude that cognitive ability plays a moderating role in path a (**Figure 1**).

This study utilized the causal step test for mediating effects (Baron and Kenny, 1986). The causal step test requires that if β_1 in Equation (2) is significant (H_0: $\beta_1 = 0$ is rejected) and γ_4 in Equation (3) is significant (H_0: $\gamma_4 = 0$ is rejected), we show that the mediating effect exists. Moreover, if γ_1 in Equation (3) is significant (H_0: $\gamma_1 = 0$ is rejected) at the same time, we get a partial mediating effect model, otherwise we get a full mediating effect model. Although the power of the causal step test method is low, the causal step test methods are very unlikely to commit a type I error (MacKinnon et al., 2002). This indicates that if the results of the casual step test are significant, the conclusion of the presence of the mediating effect can be obtained.

Assuming that the mediating effect is significant, β_3 in Equation (2) or γ_5 in Equation (3) is significant (H_0: $\beta_3 = 0$ or H_0: $\gamma_5 = 0$ is rejected), indicating that cognitive ability plays a moderating role in the indirect path (Edwards and Lambert, 2007). If β_3 is significant, cognitive ability plays a moderating role in path b (**Figure 1**). Moreover, if γ_5 is significant, cognitive ability plays a moderating role in path c (**Figure 1**).

FINDINGS

Sample Descriptive Statistics

Table 1 shows the descriptive statistics of all variables used in this study. The total number of samples was 12,032 and 12% of respondents in the total sample had purchased private medical insurance. In the whole sample, the frequency of using new media was 2.25, which was higher than that of using traditional media (2.23), which was due to the development of the Internet in China in recent years (Li and Shiu, 2012). In terms of self-rated health status and cognitive ability, the average scores of self-rated health and cognitive ability in the total sample were 3.63 and 2.45, respectively. Furthermore, the proportion of respondents that participated in social medical insurance was over 90%, which showed that the social medical insurance schemes implemented by the Chinese government were very effective (Wu et al., 2018).

This study also conducted a statistical analysis according to the frequency of traditional media and new media use (**Table 2**). When the frequency of a respondent's traditional media use exceeded the average of the total sample, they were assigned to the group named "high frequency of traditional media use." Otherwise, they were assigned to the group named "low frequency of traditional media use." A total of 5,445 samples with high-frequency use and 6,587 samples with low-frequency use of traditional media were obtained. The same method was applied to the division of the frequency of new media use. A total of 5,911 samples with high-frequency use and 6,121 samples with low-frequency use of new media were obtained. **Table 2** shows that 15% of respondents with a high frequency of traditional media use had purchased private medical insurance, whereas only 8% of respondents with a low frequency of traditional media use had purchased private medical insurance. Individuals who used traditional media with a high frequency were more likely to purchase private medical insurance than those who used traditional media with a low frequency (Browne and Kim, 1993; Karaca-Mandic et al., 2017). When it came to new media use, the same result was obtained: 20% of the group with a high frequency of new media use had purchased private medical insurance, whereas only 4% of the group with a low frequency of new media use had purchased medical insurance, and the group with a high frequency of new media use was more likely to purchase private medical insurance (Browne and Kim, 1993; Ying et al., 2007).

In terms of their self-rated health status, the respondents with a high frequency of traditional media use had an average self-rated health status score of 3.76, which was higher than the average score of 3.52 for those with a low frequency of traditional media use. Moreover, the average self-rated health score of the respondents with a high frequency of new media use was 3.91, which was also higher than the average self-rated health score of the respondents with a low frequency of new media use with 3.35. **Table 2** also shows descriptive statistics grouped by self-rated health status. When the self-rated health status of a respondent exceeded the average of the total sample, they were assigned to the group named "better self-rated health status." Otherwise, they were assigned to the group named "poor self-rated health status." A total of 6,063 samples with a better self-rated health status and 5,969 samples with a poor self-rated health status were obtained. A total of 15% of the respondents with a better self-rated health status had purchased private medical insurance compared with just 8% of respondents with a poor self-rated health status. Individuals with a better self-rated health status were more likely to purchase private medical insurance (Cooper and Trivedi, 2012; Lee, 2012).

Correlation Analysis

Correlations among dependent variable, independent variables, mediator, and moderator variables are listed in **Table 3**. According to **Table 3**, both traditional media use and new media use were significantly positively correlated with the purchase of private medical insurance. A significant positive correlation was found between media use and self-rated health

TABLE 2 | Descriptive statistics grouped by the frequency of traditional and new media use and self-rated health status.

	Traditional media use		New media use		Self-rated health status	
	High frequency of traditional media use ($n = 5,445$)	Low frequency of traditional media use ($n = 6,587$)	High frequency of new media use ($n = 5,911$)	Low frequency of new media use ($n = 6,121$)	Better self-rated health status ($n = 6,063$)	Poor self-rated health status ($n = 5,969$)
Variable	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**	**Mean**
Insurance	0.15	0.08	0.20	0.04	0.15	0.08
Traditional media use	2.85	1.71	2.35	2.11	2.31	2.15
New media use	2.59	1.96	3.36	1.17	2.56	1.93
SRH	3.76	3.52	3.91	3.35	4.34	2.90
Cog	2.68	2.25	2.89	2.02	2.67	2.22
Age	51.10	51.08	41.04	60.80	47.11	55.13
Age^2	2900	2880	1881	3862	2496	3288
Gender	0.49	0.56	0.51	0.55	0.50	0.56
Education	6.22	4.28	7.02	3.36	5.97	4.32
Marital status	0.79	0.77	0.76	0.79	0.79	0.77
Family economic status	2.70	2.43	2.71	2.39	2.72	2.38
Social medical insurance	0.94	0.91	0.92	0.92	0.92	0.93
Social endowment insurance	0.77	0.68	0.70	0.75	0.73	0.72

TABLE 3 | Correlations among study variables.

Variable	Insurance	Traditional media use	New media use	SRH	Cog
Insurance	1				
Traditional media use	0.087***	1			
New media use	0.259***	0.213***	1		
SRH	0.281***	0.252***	0.573***	1	
Cog	0.130***	0.140***	0.314***	0.336***	1

****$p < 0.01$.*

status. In addition, there was a significant positive correlation between self-rated health status and the purchase of private medical insurance.

Mediation Analysis

The regression results of mediating effect model of media use on the purchase of private medical insurance are listed in **Table 4**. Columns (1) and (4), respectively, report on the direct impact of traditional media use and new media use on the purchase of private medical insurance, namely, the test of Equation (1). Columns (1) and (4) show that the coefficients of traditional media use and new media use were 0.19 and 0.23, respectively, and both were significant at the 1% confidence level. This means that by increasing traditional media use and new media use by one scale, the probability of purchasing private medical insurance would increase by 3.09 and 3.65%, respectively. Thus, hypothesis 1 received support.

The tests for the influence of the independent variables on the mediator are reported in columns (2) and (5), where the coefficients of traditional media use and new media use were both significantly positive. This showed that the more frequently media was used, the better the self-rated status was. Since the coefficients of traditional media use and new media use in columns (2) and (5) were significant, and the coefficients of self-rated health status in columns (3) and (6) were significant, we concluded that self-rated health status had a mediating effect between media use and the purchase of private medical insurance. Meanwhile, the coefficients of the independent variables in columns (3) and (6) were both not significantly equal to zero. Therefore, self-rated health status played a partially mediating role. This implied that media use had both a direct and indirect effect on purchasing private medical insurance. On the one hand, media use had a direct positive effect on the purchase of private medical insurance (path a in **Figure 1**). On the other hand, media use promoted the individual purchase of private medical insurance by improving individuals' self-rated health status (path b and path c in **Figure 1**).

Moreover, using SPSS 26.0 Macro PROCESS (Hayes, 2013), we conducted a bootstrap procedure (number of bootstrap samples: 5,000) to analyze the direct and indirect effects of media use on the purchase of private medical insurance. The results are shown in **Table 5**. The direct and indirect effects of traditional

TABLE 4 | Regression results of mediating effect model of media use on the purchase of private medical insurance.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Insurance**	**SRH**	**Insurance**	**Insurance**	**SRH**	**Insurance**
Traditional media use	0.19***	0.13***	0.18***			
	(0.02)	(0.01)	(0.02)			
New media use				0.23***	0.10***	0.23***
				(0.01)	(0.01)	(0.01)
SRH			0.09***			0.08***
			(0.02)			(0.02)
Age	0.03***	−0.03***	0.03***	0.03***	−0.03***	0.03***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
Age^2	−0.00***	0.00***	−0.00***	−0.00***	0.00***	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Education level	0.43***	0.03	0.43***	0.38***	0.01	0.38***
	(0.04)	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)
Marital status	−0.00	0.11***	−0.02	−0.02	0.11***	−0.03
	(0.05)	(0.02)	(0.05)	(0.05)	(0.02)	(0.05)
Gender	−0.01	−0.12***	0.00	−0.00	−0.12***	0.01
	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)
Family economic status	0.24***	0.27***	0.22***	0.23***	0.27***	0.21***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Social medical insurance	−0.24***	−0.11***	−0.23***	−0.22***	−0.10***	−0.22***
	(0.06)	(0.03)	(0.06)	(0.06)	(0.03)	(0.06)
Social endowment insurance	0.20***	0.08***	0.20***	0.16***	0.07***	0.16***
	(0.04)	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)
Constant	−2.35***	0.53***	−2.39***	−2.67***	0.26***	−2.69***
	(0.18)	(0.08)	(0.18)	(0.18)	(0.08)	(0.18)
Observations	12,032	12,032	12,032	12,032	12,032	12,032
Adj R^2			0.18	0.18		
Pseudo R^2	0.11	0.13			0.12	0.14

*The robust standard errors are in parentheses. ***$p < 0.01$.*

media use on the purchase of private medical insurance were 0.33 (SE = 0.04, CI = [0.25, 0.41]) and 0.03 (SE = 0.01, CI = [0.02, 0.04]), respectively. For new media use, the direct and indirect effects were 0.41 (SE = 0.03, CI = [0.35, 0.47]) and 0.02 (SE = 0.01, CI = [0.01, 0.03]), respectively. The 95% confidence interval limits for these results did not contain zero, which was evidence that self-rated health status plays a partially mediating role between media use and the purchase of private medical insurance. Therefore, hypothesis 2 was accepted.

TABLE 5 | Direct and indirect effects of media use on the purchase of private medical insurance.

Independent variables		**Effect**	**Se**	**95% Confidence intervals**	
				LLCI	**ULCI**
Traditional media use	Direct effect	0.33	0.04	0.25	0.41
	Indirect effect	0.03	0.01	0.02	0.04
New media use	Direct effect	0.41	0.03	0.35	0.47
	Indirect effect	0.02	0.01	0.01	0.03

Bootstrap size = 5,000. Direct and indirect effects are on a log-odds metric.

Moderation Analysis

The coefficient of the interaction term between traditional media use and cognitive ability and the interaction term between new media use and cognitive ability in columns (1), (3), (4), and (6) of **Table 6** were both significantly negative. This denoted that cognitive ability played a negative moderating role in the direct path (path a in **Figure 1**). We used the regression results in **Table 6** to draw a graph (**Figure 2**) of the moderating effect of cognitive ability on path a (**Figure 1**; Dawson, 2013). **Figure 2** shows that the relationship between media use and the probability of purchasing private medical insurance was always positive. **Figure 2A** demonstrates that the probability of purchasing private medical insurance rose more for people with weak cognitive ability (the solid line). This meant that strong cognitive ability weakened the effect of traditional media use on the likelihood of purchasing private medical insurance. **Figure 2B** implies that, although cognitive ability also had a negative moderating effect on the process of using new media to promote the purchase of insurance, the moderating effect was relatively small.

Table 6 also shows that the coefficient of the interaction term between traditional media use and cognitive ability and the interaction term between new media use and cognitive

TABLE 6 | Regression results of moderated mediation model of media use on the purchase of private medical insurance.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Insurance**	**SRH**	**Insurance**	**Insurance**	**SRH**	**Insurance**
Traditional media use	0.17***	0.09***	0.16***			
	(0.03)	(0.01)	(0.03)			
New media use				0.18***	0.07***	0.18***
				(0.02)	(0.01)	(0.02)
SRH			0.05**			0.04*
			(0.02)			(0.02)
Cog	0.40***	0.20***	0.40***	0.36***	0.20***	0.35***
	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)
Traditional media use∗Cog	−0.15***	−0.08***	−0.14***			
	(0.03)	(0.01)	(0.03)			
New media use∗Cog				−0.04**	−0.07***	−0.04*
				(0.02)	(0.01)	(0.02)
SRH∗Cog			−0.03			−0.01
			(0.03)			(0.03)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,032	12,032	12,032	12,032	12,032	12,032
Adj R^2		0.20			0.20	
Pseudo R^2	0.14		0.14	0.15		0.15

*The robust standard errors are in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.*

ability in columns (2) and (5) were both significantly negative. However, the coefficient of the interaction term between self-rated health status and cognitive ability was not significant in columns (3) and (6). This indicated that cognitive ability played a negative moderating role only for path b and not for path c (**Figure 1**) in the indirect path. **Figure 3** shows the moderating effect of cognitive ability on path b (**Figure 1**; Dawson, 2013). Both traditional media use (**Figure 3A**) and new media use (**Figure 3B**) could improve an individual's self-rated health status, but this effect was far greater for individuals with weak cognitive ability (the solid line) than for those with strong cognitive ability (the dotted line). Therefore, the results supported hypothesis 3 and hypothesis 4.

Results of the Research Model

Hypothesis 1, hypothesis 2, hypothesis 3, and hypothesis 4 were supported, indicating that the moderated mediating effect model was significant. This study conducted a bootstrap procedure (number of bootstrap samples: 5,000) to further analyze the conditional direct and conditional indirect effects (Hayes, 2013). **Table 7** reports the results. Regarding the conditional direct effect of traditional media use on purchasing medical insurance, it was 0.56 (SE = 0.08, CI = [0.40, 0.73]) when cognitive ability was weak, and it was 0.11 (SE = 0.05, CI = [0.02, 0.20]) when cognitive ability was strong. And the conditional indirect effect of traditional media use on purchasing private medical insurance *via* self-rated health status was statistically significant when cognitive ability was weak (−1 SD, indirect effect = 0.03, SE = 0.02, CI = [0.01, 0.06]) compared with when cognitive ability was strong (+ 1 SD, indirect effect = 0.01, SE = 0.01, CI = [−0.01, 0.01]). Regarding the conditional direct effect of new media use on purchasing private medical insurance, it was 0.43 (SE = 0.05, CI = [0.34, 0.53]) when cognitive ability was weak, and it was 0.25 (SE = 0.04, CI = [0.18, 0.32]) when cognitive ability was strong. The conditional indirect effect of new media use on purchasing private medical insurance *via* self-rated health status was statistically significant when cognitive ability was weak (−1 SD, indirect effect = 0.02, SE = 0.02, CI = [0.01, 0.04]) compared with when cognitive ability was strong (+ 1 SD, indirect effect = 0.01, SE = 0.01, CI = [−0.01, 0.01]).

These results further supported that cognitive ability plays a negative moderating role in the direct path (path a in **Figure 1**) and the first half of the indirect path (path b in **Figure 1**) of media use on purchasing private medical insurance. After analyzing the mediation effect, the moderation effect, and the moderated mediating effect, this study gets the specific mechanism of action as shown in **Figure 4**.

ROBUSTNESS CHECK

Replacement Estimation Method

Since the purchase of private medical insurance is a binary dependent variable, the probit model was adopted previously in the study, and the logit regression model was used for the presently discussed robustness check. The regression results are shown in **Supplementary Table 1**, and the conclusions were significant and robust. Media use had a positive impact on the purchase of private medical insurance, and the self-rated health status played a partially mediating role. Paths a and b in **Figure 4** were negatively moderated by individual cognitive ability.

Winsorizing

To alleviate the influence of outliers on parameter estimations, this study winsorized the independent variables at 2.5 and 97.5%.

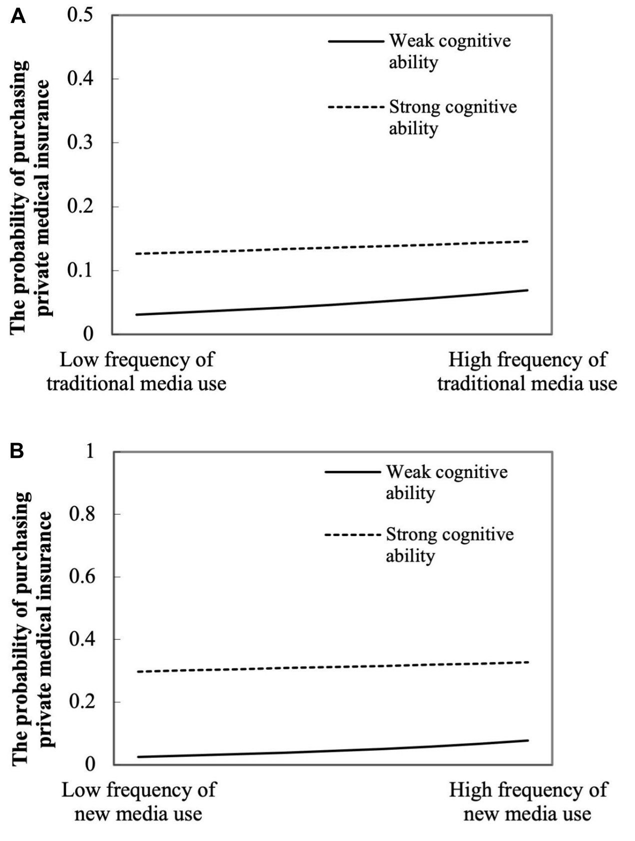

FIGURE 2 | Moderating effect of cognitive ability on media use on the probability of purchasing private medical insurance. **(A)** Traditional media use; **(B)** new media use.

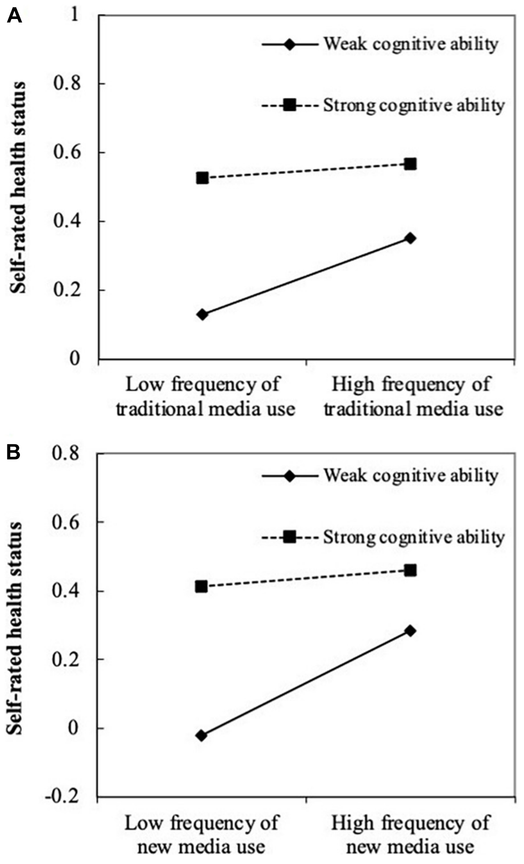

FIGURE 3 | Moderating effect of cognitive ability on media use to self-rated health status. **(A)** Traditional media use; **(B)** new media use.

Supplementary Table 2 reports the regression results, which were also robust.

Adding Control Variables

This study conducted a robustness test by increasing the control variable of social trust (Brown and Goolsbee, 2000). Social trust is an important factor in behavioral economics, where an individual's trust in society will affect their judgment of social information, thus affecting their decision-making behavior. Social trust can effectively alleviate moral hazards and adverse selection problems when participating in medical insurance, which is beneficial for individuals when purchasing private medical insurance (Atim, 1999). The variable of social trust was composed of five scales. The higher the value was, the higher the level of trust the interviewees had in society. The regression results were significant and robust, as shown in **Supplementary Table 3**.

Culling the Sample

Considering that the elderly use the Internet less (Bundorf et al., 2006), this study dropped the samples of respondents over 65 years old. The regression results are shown in **Supplementary Table 4**, where the regression results were still consistent with the previous ones after excluding people over 65 years old.

DISCUSSION

This study investigates the relationship between media use and the purchase of private medical insurance and their internal mechanism. As in hypothesis 1, the regression results of this study indicate that individuals' use of traditional media or new media facilitated the purchase of private medical insurance. This finding is consistent with previous studies, which found that with an increasing frequency of media use, individuals are more likely to get insurance-related information (Cheong, 2007; Furtado et al., 2016), thus, are more likely to purchase insurance (Karaca-Mandic et al., 2017). Interestingly, we found that new media use promoted the purchase of private medical insurance more than traditional media use. The reason for this phenomenon could be that the Internet penetration rate in China has exceeded 70%, according to the China Statistical Yearbook 2021, and residents in some remote rural areas can use mobile phones to access the Internet at any time and from any location. In their daily lives, individuals spend far more time using new media than traditional media. In addition, when

TABLE 7 | Conditional direct and conditional indirect effects of media use on the purchase of private medical insurance.

Independent variables		Level of cognitive ability	Effect	Se	95% Confidence intervals	
					LLCI	ULCI
Traditional media use	Conditional direct effect	−1 SD	0.56	0.08	0.40	0.73
		Mean	0.34	0.05	0.23	0.44
		+ 1 SD	0.11	0.05	0.02	0.20
	Conditional indirect effect	−1 SD	0.03	0.02	0.01	0.06
		Mean	0.02	0.01	0.01	0.02
		+ 1 SD	0.01	0.01	−0.01	0.01
New media use	Conditional direct effect	−1 SD	0.43	0.05	0.34	0.53
		Mean	0.34	0.03	0.28	0.41
		+ 1 SD	0.25	0.04	0.18	0.32
	Conditional indirect effect	−1 SD	0.02	0.02	0.01	0.04
		Mean	0.01	0.01	0.01	0.02
		+ 1 SD	0.01	0.01	−0.01	0.01

Bootstrap size = 5,000. Direct and indirect effects are on a log-odds metric.

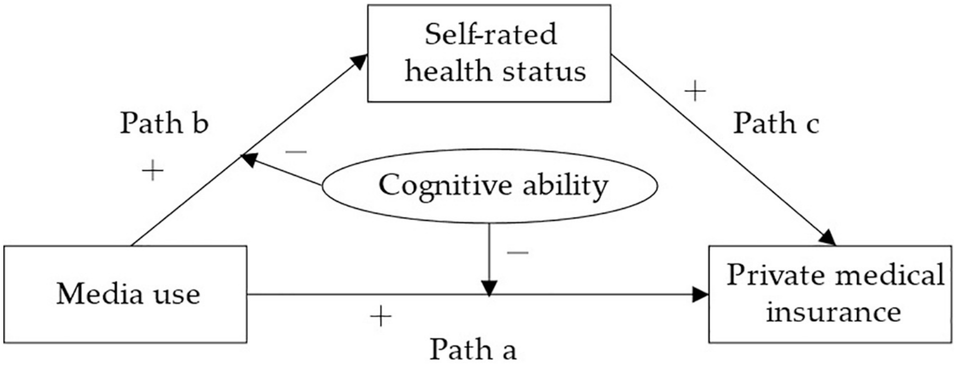

FIGURE 4 | Influence mechanism diagram.

individuals see some news about health, risk, and insurance and want to purchase private medical insurance, they can do so online through the websites of insurance companies and insurance brokerage companies. When compared to purchasing insurance from an insurance agent in person, purchasing insurance online is more convenient and faster.

In addition, individual social trust, social interaction, and financial literacy improve with the increase in media use frequency, which drives them to purchase private medical insurance (Browne and Kim, 1993; Manski, 2000; Beiseitov et al., 2004; Liu et al., 2014). To further analyze the influence mechanism of media use on purchasing private medical insurance, we explored whether their relationship was mediated by individuals' self-rated health status and whether the direct and indirect paths were moderated by individuals' cognitive ability. We found that self-rated health status was played a partially mediating role between media use and the purchase of private medical insurance. Self-rated health status was positively correlated with media use and the purchase of private medical insurance. The direct and indirect paths from media use to the purchase of private medical insurance were negatively moderated by cognitive ability. Weak cognitive ability enhanced the direct effect of media use on purchasing private medical insurance and the indirect effect of media use on purchasing private medical insurance *via* self-rated health status.

Mediating Role of Self-Rated Health Status

As in hypothesis 2, self-rated health status plays a partially mediating role and potential reasons might be attributed to the following. The media can provide individuals with information about physical and mental health and medical resources so that individuals can obtain rich health-related knowledge (Kim and Oh, 2012; Jiang and Street, 2017). People can also receive professional advice from some healthcare systems on issues such as eating habits, healthy lifestyles, and so on, to improve their physical quality of life. Compared with traditional media, the Internet can provide people with online expert consultation that is not limited by time and place, so that people can get a timely judgment of their health status, relieve their anxiety about their own body, and then obtain a better self-rating of their health status (Li et al., 2020). Furthermore, some studies have discovered that people who use the Internet to communicate with friends and build a harmonious social network have better mental health (Bessiere et al., 2010; Wellman et al., 2016). For some people who are often anxious, using the media to browse some entertainment news can divert their attention and reduce the symptoms of anxiety.

In addition, self-rated health status is often used as a measure of risk on the grounds (Hurd and McGarry, 1995; Idler and Benyamini, 1997). Studies have shown that people who have a better self-rated health status tend to do fewer risky things in life (Doiron et al., 2008). This type of person is risk averse and their desire for insurance is very high. Therefore, there may be a positive relationship between self-rated health status and the probability of purchasing private medical insurance. Moreover, individuals' income is related to their health status, and those with a better self-rated health status are generally more likely to be employed and to have a sustained income than those with a poor self-rated health status. If they feel their future income is not sustainable and the premiums are not affordable, they may not choose to purchase private medical insurance (Yue and Zou, 2014). There is another reason for self-rated health status as a mediator. When people use the media to obtain information about health and insurance, they learn that people with poor health status will be rejected from purchasing private medical insurance. People with better health status worry about their future health status becoming poor and purchase private medical insurance in advance.

Moderating Role of Cognitive Ability

As in hypothesis 3 and 4, this study found that individual cognitive ability negatively moderated the direct and indirect pathways of media use on purchasing private medical insurance. In the direct path, cognitive ability mitigated the positive effect of media use on purchasing private medical insurance. This phenomenon could be explained by the fact that people with strong cognitive ability were more cautious about insurance-related information (De keersmaecker and Roets, 2017). This leads to higher requirements for products and services for people with strong cognitive ability (Jhang et al., 2012). For the same insurance advertisement, they will be likely to find some flaws in private medical insurance due to their higher requirements. There are only a few private medical insurance products that can meet their requirements, which makes it more difficult to promote the purchase of private health insurance among them. However, it is quite interesting that the positive effect of new media use on purchasing private medical insurance is less negatively moderated by cognitive ability than traditional media use. This may be because, compared with traditional media, one of the advantages of new media is that people can search for relevant information at will, so that people are less affected by particular information. Thus, people can have a more comprehensive understanding of insurance and risk.

Meanwhile, the first half (path b in **Figure 4**) of the indirect effect was negatively moderated by cognitive ability. This was because people who had weak cognitive ability may overstate their health status (Tsendsuren et al., 2018). People with strong cognitive ability do not entirely trust media information about physical and mental health. They can examine the source and authenticity of the information and make more careful judgments about their health (De keersmaecker and Roets, 2017). Additionally, individuals who had strong cognitive ability were less optimistic about the true state of their physical and mental health. Therefore, as the frequency of media use increased, the self-rated health status of individuals with strong cognitive ability increased less than that of individuals with weak cognitive ability. In addition, interestingly, although the coefficient of the interaction term between self-rated health status and cognitive ability was not statistically significant, the coefficient value was negative. This may also indicate that people with strong cognitive ability have higher requirements for private medical insurance products, which may inhibit their demand for private medical insurance to some extent.

Limitations and Future Directions

Due to the limitation of data, this study still had some deficiencies. First, the variable of cognitive ability in this study only included individuals' verbal abilities and excluded mathematical and spatial abilities, which means that the measurement of cognitive ability may not have been comprehensive enough. Second, the CGSS2017 only included private medical insurance, without indicators for private health insurance. Finally, this study only analyzed the mechanism of the influence of media use on whether residents purchased private medical insurance but did not analyze the influence of media use on private medical insurance premium expenditure. Future studies can explore the mechanism of the influence of media use on the purchase of private health insurance and premium expenditure.

CONCLUSION AND IMPLICATIONS

The implementation of the social medical insurance policies (UEBMIS, NCMS, and URBMIS) in China has been very effective, but the coverage rate for private medical insurance is still very low. This study aimed to better explore the factors affecting the demand for private medical insurance and improve the coverage of private medical insurance in China. Based on the data of CGSS2017, this study found that media use had a significant positive impact on the purchase of private medical insurance, which is consistent with the conclusions of some previous studies. However, this study innovatively took self-rated health status as a mediating variable and took cognitive ability as a moderating variable to construct a moderated mediation model. The regression results showed that both mediating and moderating effects were significant. Media use directly and indirectly promoted the purchase of private medical insurance among individuals by improving their self-rated health status. Moreover, cognitive ability played a negatively moderating role in the direct path and the first half (path b in **Figure 4**) of the indirect path.

The theoretical contribution of this paper is to study the influencing factors of the purchase of private medical insurance on the basis of the TPB and HBM theories. Moreover, CGSS data are used to supplement the empirical research of the TPB and HBM theories using a moderated mediation effect model. Furthermore, this study can help us to better understand how media use influences the purchase of private medical insurance and provides a theoretical reference for governments around the world to publicize insurance knowledge through the media. From the perspective of practical contribution, this study will also provide help for insurance companies to adjust their advertising strategies. With the development of Internet media, the frequency of residents using the Internet media is increasing. Insurance companies can cooperate with Internet media, such as TikTok, Twitter, and Facebook, to deliver accurate insurance advertisements using big data analysis.

DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: http://cgss.ruc.edu.cn/.

AUTHOR CONTRIBUTIONS

HS: conceptualization, methodology, software, formal analysis, writing–original draft preparation, and visualization. LG: methodology, validation, formal analysis, and visualization. GW: validation and funding acquisition. All authors contributed to manuscript revision, read, and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.894195/full#supplementary-material

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Understanding the Antecedents of the Routine Use of Mobile Health Services: A Person–Technology–Health Framework

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Although numerous studies have been conducted to understand the antecedents of usage of mobile health (mHealth) services, most of them solely focus on characteristics of mHealth services themselves but neglect taking users' psychological and health-related factors into consideration. Besides, the comprehensive understanding of what influences users' routine use intentions regarding mHealth services is lacking. Therefore, this study proposes a person–technology–health framework that underlines how personal factors (e.g., personal innovativeness in IT), technological factors (e.g., trust), and health factors (e.g., perceived health severity) jointly influence individuals' routine use intentions regarding mHealth services. The proposed research model and related hypotheses were tested based on survey data from 270 respondents. The results indicate that personal innovativeness in IT, trust, and perceived health severity are important for enhancing routine use intention of mHealth services. Specifically, in situations of high perceived health severity, trust relates less positively to routine use intention than personal innovativeness in IT. In contrast, in situations of low perceived health severity, trust relates more positively to routine use intention than personal innovativeness in IT. The research findings extend the existing literature on routine use intention related to mHealth services and provide significant implications for practitioners.

Keywords: mHealth services, personal innovativeness in IT, trust, perceived health severity, routine use intention

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INTRODUCTION

Empowered by mobile information communication technology, mobile health (mHealth) services as emerging health-related information technology can deliver timely and ubiquitous health information and services to individuals based on individual-tailored healthcare needs (Akter and Ray, 2010; Akter et al., 2011). The increasing population with chronic diseases and multi-morbidities in recent years calls for an increase in the routine use of mHealth services. Because mHealth services have shown great potential for improving patient wellbeing, mental health, health management, and distribution of medical resources (Hoque and Sorwar, 2017; Zhao et al., 2017; Oliveira et al., 2021). Furthermore, the application of mHealth services in the diagnosis and treatment of infectious diseases could improve outbreak detection, disease surveillance, and guide a precise response of public health (Wood et al., 2019). However, achieving these outcomes highly depends on users' sufficient data based on daily interactions (Deng et al., 2014; Zhao et al., 2017). Therefore, to increase both user stickiness and developers' profits, it is more important to enhance existing users' day-to-day use as a form of routine use than it is to acquire more mHealth users (Li et al., 2013; Meng et al., 2019b). However, the routine use of mHealth services remains at a lower level, in particular, the daily use rate is 5.7% and the weekly use rate is 30.6% based on a recent work of Knitza et al. (2020). To this end, it is urgent to understand what influences users' routine use of mHealth services.

Existing literature is abundant in investigating various antecedents of the adoption and uses intention of mHealth services. These include both technological factors (individuals' evaluations of mHealth), such as perceived usefulness, perceived ease of use, perceived trustworthiness, and perceived value (Sun et al., 2013; Deng et al., 2014; Okazaki et al., 2015; Fox and Connolly, 2018; Alam et al., 2020) and personal factors (individuals' personality traits) like personal innovativeness in IT (PIIT), technology anxiety, self-efficacy, and privacy concerns (Rai et al., 2013; Deng et al., 2014; Guo et al., 2016; Reychav et al., 2019). In a typical professional setting, such as health services, however, users may exhibit interesting or fundamental differences from ordinary business user groups, in part because of their health conditions (Chau and Hu, 2002; Gorini et al., 2018). The use of mHealth services has also been examined from the perspective of Protection Motivation Theory (PMT), which suggests that users are willing to use mHealth services to improve their health status in order to avoid health threats, such as chronic diseases (Rai et al., 2013; Zhao et al., 2017). These studies and others indicate that health-related factors (individuals' evaluations of their health conditions), such as perceived physical condition, perceived severity, perceived vulnerability, and health rationality, significantly influence adoption and use intention of mHealth services (Deng et al., 2014; Guo et al., 2015; Zhao et al., 2017; Zhang et al., 2020).

In this light, we consider these three categories of factors to be salient antecedents for predicting individuals' attitudes and behaviors regarding mHealth services. However, only a limited number of studies in the extant mHealth literature consider how these factors jointly affect the routine use of mHealth services (Deng et al., 2015; Zhao et al., 2017; Meng et al., 2021). Moreover, to the best of our knowledge, no studies integrate and underline the interactions among those factors to comprehensively understand the routine use of mHealth services. It is thus imperative to narrow this research gap by developing a more comprehensive research framework, which can theoretically integrate these factors in order to predict mHealth service adoption and use in general and routine use in particular (Rai et al., 2013; Meng et al., 2019b, 2020).

Drawing upon relevant literature on mHealth services and health informatics, we therefore propose an integrative person–technology–health (PTH) research framework to predict routine use of mHealth services by testing the interaction effects of technological factors, personal factors, and health factors on routine use intention. Accordingly, PIIT, trust, and perceived health severity are theoretically identified as three critical factors of the PTH framework and integrated into a research model. Here, mHealth services refer to healthcare delivery through mobile information technology, which require users' high level of engagement to access timely personalized health services for improved health conditions (Akter et al., 2013a). Therefore, we believe that the PTH framework is particularly appropriate for predicting routine use of mHealth. Theoretically, our study is one of the first to propose and empirically investigate the combined effects of technological, personal, and health factors on routine use intention of mHealth services based on the PTH framework. In addition, this integrative PTH framework provides insights into other contexts of health-related IT adoption and usage and thus may be valuable in future studies. In practice, mHealth service providers can take advantage of the PTH framework to precisely customize their marketing strategies based on the joint effects of trust, PIIT, and perceived health severity to increase their users' stickiness as a form of routine use and obtain long-term benefits.

The remainder of this paper proceeds as follows. First, we discuss the previous literature on various factors of the PTH framework. Then, we present the proposed research framework and hypotheses, followed by the research methodology and data analyses. Finally, we report the key findings, implications for research and practice, and limitations of our work.

LITERATURE REVIEW

Factors of the PTH Framework

Our study develops the PTH framework based on the mHealth services literature and the health informatics literature. Prior studies of mHealth service adoption and usage were conducted based on a small number of well-worn and conceptually interrelated theories, such as the theory of planned behavior (Ajzen, 1991), technology acceptance model (Davis, 1989; Venkatesh et al., 2002), motivational model (Davis et al., 1992), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003). As shown in **Table 1**, previous studies mainly examine the effects of technological factors (e.g., perceived usefulness, perceived ease of use, and trust) and personal factors (e.g., perceived behavioral control, computer self-efficacy, and technology anxiety) on mHealth service adoption and usage (Chen et al., 2018; Balapour et al., 2019; Cocosila and Turel, 2019; Alam et al., 2020). On the other hand, studies within the health informatics literature have demonstrated that health factors, such as health status and perceived health conditions, are significantly associated with the use of health IT (Rai et al., 2013; Deng et al., 2014; Cho et al., 2014b; Lagoe and Atkin, 2015; Meng et al., 2021). All these factors can be categorized according to the PTH framework, thus indicating the appropriateness of this conceptual framework for understanding critical antecedents of mHealth service use.

According to our summary of extant literature on mHealth service adoption and usage (see **Table 1**), three research gaps need to be filled. First, with some exceptions (Deng et al., 2014;

TABLE 1 | Factors of the PTH framework in prior studies.

Literature	Topic	Factors of the PTH framework			Dependent variable	Two-way interacti
		Technological factor	**Personal factor**	**Health factor**		
Wu et al., 2011	mHealth services	Perceived usefulness; perceived ease of use; perceived service availability	Perceived behavioral control; personal innovativeness in IT;		Behavioral intention	No
Guo et al., 2012	mHealth services	Perceived usefulness; perceived ease of use	Technology anxiety; resistance to change		Adoption intention	No
Cocosila, 2013	mHealth services	Extrinsic motivation; intrinsic motivation; perceived risk	*A priori* attitude toward the activity		Behavioral intention	No
Rai et al., 2013a	mHealth services		Personal innovativeness toward mobile services; socioeconomic status and demographics	Perceived health conditions	Usage intentions and channel preferences	Yes
Akter et al., 2013b	mHealth services	Perceived usefulness; perceived service quality; perceived trust			Continuance intention	No
Cho et al., 2014a	Health application	Perceived usefulness; perceived ease of use	Health consciousness; health information orientation; eHealth literacy; health application use efficacy		Behavioral intention to use	No
Deng et al., 2014	mHealth services	Perceived value	Perceived behavioral control; resistance to change; self-actualization need; technology anxiety	Perceived physical condition	Behavioral intention	No
Shareef et al., 2014	mHealth services	Perceived usefulness; perceived privacy and security; perceived ease of use; perceived compatibility; perceived reliability			mHealth adoption	No
Deng et al., 2015	mHealth services	Information quality; perceived value; trust	Personal health value	Current health status	Use intention	Yes
Guo et al., 2015	mHealth services		Response efficacy; self-efficacy; age; gender	Perceived vulnerability; perceived severity	Behavioral intention	Yes
Okazaki et al., 2015	mHealth monitoring systems	Perceived value; overall quality; net benefits	Prior mobile internet experience		Usage intention	Yes
Guo et al., 2016	mHealth services	Trust	Privacy concern; personalization concern; age		Adoption intention	No
Zhao et al., 2017	mHealth services	Perceived usefulness; perceived ease of use; trust; perceived risk	Perceived behavioral control; age	Perceived vulnerability; perceived severity	Behavioral intention	Yes
Deng et al., 2018	mHealth services	Perceived usefulness; perceived ease of use; trust; perceived risk			Adoption intention	No
Fox and Connolly, 2018	mHealth services	Risk beliefs; trust beliefs	Mhealth self-efficacy; Information seeking experience; health information privacy concerns		Adoption intention	No
Chen et al., 2018	Mobile health application	Perceived usefulness; trust in app	Privacy concern		Continuance intention	Yes
Balapour et al., 2019	mHealth apps	Mobile technology identity	Related IT expertise; self-efficacy		Intention to use	No
Meng et al., 2019b	mHealth services	Argument quality; source credibility	Health consciousness		Routine use intention	Yes
Cocosila and Turel, 2019	mHealth services	Extrinsic motivation; intrinsic motivation; adoption risk; non-adoption risk			Adoption intention	No
Zhang et al., 2020	Mobile monitoring services	Device satisfaction; feedback satisfaction	Emotional attachment	Health rationality	Mobile monitoring services usage	Yes
Meng et al., 2021	mHealth services	Cognitive trust; affective trust	Technology anxiety	Health anxiety	Continuance use intention	Yes

Zhao et al., 2017), many studies failed to integrate person, technology, and health factors into a single research framework and simultaneously test their direct effects on mHealth service adoption and use. Second, although some scholars examined either the interaction effects of technological factors and personal factors (Okazaki et al., 2015; Chen et al., 2018) or the interaction effects of personal factors and health factors on mHealth service adoption and use (Rai et al., 2013), most scholars failed to investigate the interactions among all three factors to predict mHealth service adoption and use. Third, to our best knowledge, scant research exists to examine mHealth users' routine use based on a comprehensive framework involving technological, personal, and health-related factors. In order to fill these research gaps, we intend to integrate all of the aforementioned factors into one single research framework. We test not only the direct effects of personal factors, technological factors, and health factors but also the interaction effects among them on routine use intention, thus further advancing our understanding of users' routine use intention regarding mHealth services.

Interaction Between Personal Factors and Technological Factors

The interaction between personal factors and technological factors has been extensively studied in the prior information systems literature. Personal evaluations of technology (e.g., perceived usefulness, perceived ease of use, and trust in IT) are directly derived from the interactions between users and technology. This perspective is supported by the innovation-values fit theory, which refers to the extent to which users perceive that the use of the innovation is congruent with users' values by assessing "the objective characteristics of an innovation and its socially constructed meaning" (Klein and Sorra, 1996, p. 1063). In other words, an individual's use of a technology is determined by the level of the fit between the innovation and her/his value (Klein and Sorra, 1996).

The effects of this interaction on mHealth service adoption and usage have been examined by several scholars. Okazaki et al. (2015) examined the moderating effects of users' experience on perceived value and found that users with prior mobile internet experience will perceive greater value in using an mHealth monitoring system than those without relevant experience, thus leading to a higher probability that these more experienced technology users will use mHealth services. Some scholars selected age and gender as moderators in their mHealth service adoption study, and their results indicated that compared to younger users, middle-aged and older users pay more attention to perceived ease of use and effort expectancy when they are making adoption decisions (Zhao et al., 2017; Nunes et al., 2019). Chen et al. (2018) found that both trust in apps and perceived usefulness are positively associated with continuing use intention regarding mHealth apps, and privacy concerns enhance the effects on continuous use intention. Meng et al. (2019b) found that individuals with higher levels of health consciousness are more willing to rely on source credibility than argument quality to inform their routine use of mHealth services. On the basis of these studies, the extent to which technological factors influence mHealth service adoption and use is contingent on personal factors because mHealth services are defined as personalized and interactive. Therefore, it is necessary to investigate the interaction effects of technological and personal factors to comprehensively understand routine use intention regarding mHealth services.

Interaction Between Health Factors and Technological Factors

Prior literature indicates that health factors are significantly associated with the use and adoption of health IT. Many of these studies are based on Protection Motivation Theory (PMT), which proposes that individuals' threat appraisals (e.g., their perceived severity and perceived vulnerability) and coping appraisals (e.g., response efficacy, self-efficacy, and response costs) are two dominant predictors of health behaviors (Rogers, 1975). Perceived severity refers to the seriousness of a specific threat while perceived vulnerability refers to the probability that one will experience harm (Rogers, 1975). Perceived vulnerability and perceived severity are often combined to measure perceived threat; however, the unique relationship of each to health behavior has also been investigated (Witte, 1992; McKinley, 2009; Zhao et al., 2017). Accordingly, individuals with poor health conditions are more likely to use health IT to improve their health status (Houston and Allison, 2002; Baker et al., 2003; Rai et al., 2013; Xiao et al., 2014). Also researching these effects, Guo et al. (2015) found that among women and the elderly, perceived severity and perceived vulnerability strongly influence individuals' attitudes toward using mHealth services. Zhao et al. (2017) indicated that perceived vulnerability and perceived severity are significant factors in predicting middle-aged and older users' use of mHealth services.

Researchers have also explored the role of health anxiety: individuals who feel anxious about their health conditions show greater inclination to seek out online health information (Baumgartner and Hartmann, 2011; Lagoe and Atkin, 2015; te Poel et al., 2016). For example, Baumgartner and Hartmann (2011) found that individuals with a high level of health anxiety experience more negative consequences from searching for health information online. However, the findings in this area are inconsistent. For instance, Xue et al. (2012) found that female users' perceived health conditions have no direct effects on perceived usefulness, perceived ease of use, and perceived compatibility of mHealth apps.

To the best of our knowledge, however, there has been little research on the interaction effects between health factors and technological factors on the use and adoption of mHealth services. There are some exceptions, including Deng et al. (2015), who found that individuals with poor health status (e.g., mental or physical illness) rely more on trusted health information providers and are more eager to use mobile phones to get health information with the purpose of improving their health. Meng et al. (2021) demonstrated that health anxiety increase the effects of cognitive trust but alleviate the effect of affective trust on continuous intention of mHealth services use.

Considering that health services closely relate to people's life quality (Fichman et al., 2011), individuals with various health conditions may hold various attitudes toward using a target health IT, such as an mHealth service, in the long run. Therefore, it is urgent for mHealth scholars to investigate the interaction effects of health and technological factors on routine use.

Interaction Between Personal Factors and Health Factors

Studies have indicated that both individuals' personal and health-related factors are important predictors of health-related behaviors and technology adoption in the health behavior context. Based on the basic tenet of the health belief model (Rosenstock, 1974; Janz and Becker, 1984), the health-promoting behaviors of individuals with different socio-demographic characteristics are determined by their beliefs about health conditions (e.g., perceived severity and perceived susceptibility), perceived benefit, and perceived barriers (Hochbaum et al., 1952). Moreover, personal factors, such as age, gender, race, socioeconomic status, and characteristics, also influence individuals' health-related behavior (Carroll et al., 2017).

Some scholars examined the interactions of personal and health-related factors in the context of mHealth service adoption and usage. Rai et al. (2013a) indicated that personal innovativeness toward mobile services (PIMS) has positive moderating effects on perceived health conditions comprising perceived healthiness and perceived vulnerability. Moreover, the interactions of consumers' PIMS and perceived health conditions have significant positive effects on mHealth service usage intentions, assimilation, and channel preferences (Rai et al., 2013). Guo et al. (2015) found that personal factors (e.g., gender and age) have different effects on threat appraisals (perceived vulnerability and perceived severity) and coping appraisals (response efficacy and self-efficacy) in the acceptance of mHealth services. For example, the female and the elderly are more willing to form positive attitudes and accept mHealth services when they perceive higher levels of vulnerability and severity. Similarly, Zhao et al. (2017) found that perceived vulnerability and perceived severity are more significant predictors of mHealth service use among middle-aged and older users. However, the interaction effects of personal and health factors on the routine use of mHealth services still remain unexplored, thus calling for additional research.

RESEARCH MODEL AND HYPOTHESES

According to previous work on the adoption and use of mHealth services, personal factors [e.g., PIIT (Lu, 2014)], technological factors [e.g., trust (Deng et al., 2018)], and health-related factors [e.g., health severity (Or and Karsh, 2009)] have been identified as significant factors influencing mHealth adoption and use. However, interaction effects and combined effects of personal factors, technological factors, and health-related factors on mHealth routine use have not been fully investigated. To comprehensively understand antecedents of mHealth routine use, drawn upon information system and health informatics literature, we propose the PTH research framework (**Figure 1**) that incorporates constructs of trust, PIIT, and perceived health severity to investigate routine use intention. First, we propose that these three variables have direct effects on routine use intention (H1, H2, and H3). Second, we test the moderating effects of perceived health severity on the associations between two components and routine use intention (H4 and H5). Finally, we test the moderating effect of PIIT on the association between trust and routine use intention (H6).

Technological Factor: Trust

Trust in technology refers to a person's judgment or expectation that a given technology's helpfulness, reliability, and functionality will support them in their work (Thatcher et al., 2011). As trust can reduce risks and uncertainties, it plays a significant role in the adoption of a new IT (Kim and Prabhakar, 2004). Prior studies underscore the fact that trust is a significant prerequisite of social behavior and positively associated with users' use intentions in multiple contexts: an internet store (Jarvenpaa et al., 1999), purchasing books on the internet (Gefen, 2000), e-government services (Carter and Bélanger, 2005; Lim et al., 2012), e-commerce (Gefen et al., 2003; Pavlou, 2003; Palvia, 2009), and health informatics (McKinley and Ruppel, 2014; Xiao et al., 2014).

Scholars studying mHealth service adoption and usage have found that trust significantly influences users' intentions to use mHealth services (Deng et al., 2015; Guo et al., 2016; Zhao et al., 2017). For example, Guo et al. (2016) found that trust in mHealth service providers enables the reduction of individuals' privacy concerns and an increase in adoption intentions. Zhao et al. (2017) and Meng et al. (2019a) indicated that trust is positively associated with the behavioral intention to use mHealth services. In their study, Deng et al. (2018) confirmed trust as an important positive and technical factor predicting users' adoption intention regarding mHealth services. In the post-adoption stage, perceived trust in mHealth services is proved to have strong effects on satisfaction and continuance intentions (Akter et al., 2013b). Similarly, Meng et al. (2021) found that both cognitive and affective trust strongly affect elderly users' continuous use intention of mHealth services. Furthermore, considering that mHealth services are credence goods, most people have limited knowledge and experience for forming clear perceptions and beliefs. Based on the above statements, individuals will have greater intention to routinely use a more trusted mHealth service. Thus, we hypothesize that:

> *Hypothesis 1*: Trust increases individuals' routine use intentions regarding mHealth services.

Personal Factor: PIIT

Personal innovativeness in IT (PIIT) refers to an individual's willingness to try out any new information technology (Agarwal and Prasad, 1998). PIIT is regarded as the most effective determinant of innovation adoption because it reflects an individual's natural reaction toward a new technology in multiple

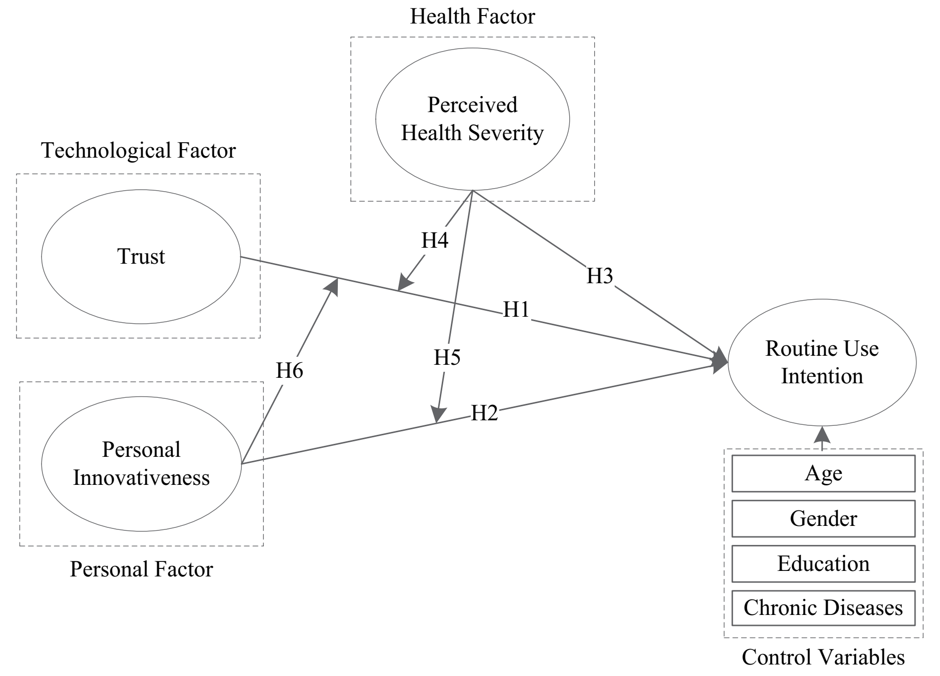

FIGURE 1 | The research model.

adoption domains (Lu, 2014). As personal innovativeness is an individual-specific trait, those who are more innovative are likely to develop positive attitudes toward an innovation and use it (Agarwal and Prasad, 1998). According to Lu et al. (2008), individuals with higher PIIT are more prone to be risk-seeking and may develop more positive intentions to adopt or use an innovation. Among personal psychological factors, PIIT has been widely proved as a critical predictor of behavioral intentions by previous studies on m-commerce (Aldás-Manzano et al., 2009; Zarmpou et al., 2012; Zhao et al., 2012). Prior studies of mHealth services demonstrated that PIIT is positively related to an individual's intention to use mHealth (Wu et al., 2011; Rai et al., 2013). In addition, innovativeness may play an important role because mHealth services are still in the early stage of development and implementation (Lee, 2016). We therefore believe PIIT is an influencing variable in predicting individuals' routine use intentions regarding mHealth, and we hypothesize that:

> *Hypothesis 2*: PIIT increases individuals' routine use intentions regarding mHealth services.

Health Factor: Perceived Health Severity

According to the PMT, perceived vulnerability refers to the probability that one will experience harm, while perceived severity refers to the seriousness of a specific threat (Rogers, 1975). When individuals suffer from health-related threats, they are more likely to use new health IT in order to reduce or avoid those threats (Prentice-Dunn and Rogers, 1986). Prior research also suggests that perceived severity is associated with healthy behavior, such as healthy eating, use of online mental health resources, and use of mobile health services (McKinley, 2009; Sun et al., 2013; McKinley and Ruppel, 2014). Distinct from other services, the eventual purpose of accessing health services through health information technology is to improve individuals' life quality and health conditions (Or and Karsh, 2009). Therefore, individuals with high health severity or in poor health conditions have stronger willingness to adopt and use health information technology with the aim of alleviating threat of diseases than other health-related factors (DiMatteo et al., 2007). Accordingly, we propose health severity as a primary determinant of adoption and use of mHealth services.

In the context of mHealth services, according to the work of Rai et al. (2013a), people who are afflicted with chronic diseases (e.g., diabetes, heart disease, cancer, high blood pressure, and stroke) are more willing to use mHealth services to manage their health. Guo et al. (2015) demonstrated that users' perceived vulnerability and perceived severity significantly influence their attitudes toward mHealth services. Zhao et al. (2017) found that elderly users have more concern about their health issues, and they are more likely to use mHealth services to get rid of illness threats and stay healthy. Therefore, we can expect that when the perceived seriousness of a health-related threat is higher, individuals are more prone to routinely use mHealth that can minimize or eliminate the threat. Accordingly, we propose that:

> *Hypothesis 3*: Perceived health severity increases individuals' routine use intentions regarding mHealth services.

Interaction Effects Among Trust, PIIT, and Perceived Health Severity

Based on our previous discussions, we can expect that an individual with a higher degree of perceived health severity is more willing to try out mHealth and use it routinely, especially when they perceive mHealth can be trusted to improve her or his healthcare outcomes. As a consequence, we propose two-way interaction effects among trust, PIIT, and perceived health severity on routine use intention.

With respect to the interaction effects of trust and perceived health severity on routine use intention, an individual with serious health conditions may choose to use mHealth routinely to reduce the threat of disease and stay healthy. However, these users may not have the level of health literacy that a health professional would have, and health literacy is important in evaluating the information and services provided by mHealth (Anderson and Agarwal, 2011; Cho et al., 2014a). Further, consumers with poor health conditions have a high probability to seek health information through a trustworthy mobile application (Deng et al., 2015), this is because health behavior outcomes are positively determined by health seeking behavior (Anker et al., 2011). In this vein, users have a higher level of health severity may rely on the trust in mHealth services than those with a lower level of health severity. Therefore, to minimize the possibility of uncertainty and risk, these users will be more likely to routinely use a trustworthy mHealth platform. Accordingly, the positive relationship between trust in mHealth and routine use intention can be strengthened by health severity, we propose that:

> *Hypothesis 4*: Perceived health severity strengthens the positive association between trust and individuals' routine use intentions regarding mHealth services.

On the other hand, an individual with a higher level of PIIT is more likely to try out any new health IT (e.g., mHealth) as complement or substitute to in-person health services to avoid or reduce the health-related threat when they perceive higher health severity (Lagoe and Atkin, 2015; Zhao et al., 2017). In this situation, the effect of PIIT on routine use intention regarding mHealth services will be increased by health severity. On this basis, we hypothesize that:

> *Hypothesis 5*: Perceived health severity strengthens the positive association between PIIT and individuals' routine use intentions regarding mHealth services.

With regard to PIIT, users with a higher level of PIIT may easily to evaluate mHealth's helpfulness, reliability, and functionality while they are using this service. Besides, previous studies have proved that individuals with higher PIIT often have higher levels of technology use (Citrin et al., 2000; Goldsmith, 2001, 2002). Accordingly, an innovative mHealth user can easily develop trust that mHealth services will enhance her/his health outcome and alleviate the disease threat, thus leading to routine use intentions. In such a situation, the positive association between trust in mHealth and routine use intention can be strengthened by PIIT. On this basis, we hypothesize that:

> *Hypothesis 6*: PIIT strengthens the positive association between trust and individuals' routine use intentions regarding mHealth services.

METHODOLOGY

This study is based on a leading mobile health service company, Ciyun. cn, in China. Ciyun health technology company was founded in August 2014. The core product includes "one platform and two applications." The platform is the data intelligent platform which collects, cleans, converts, and labels personal health data to support two applications for serving medical institutions, enterprises, and the government. The number of users on the Ciyun mHealth service platform was over 2 million by 2020. The functions of the platform include online medical consultation, routine appointments in the out-patient clinic, returning visits, medicine reminders, medical records, real-time positioning, etc. Therefore, this target company was an appropriate site for data collection. The questionnaire is randomly distributed to 292 users through Ciyun mHealth service apps. Permission was obtained, and proper arrangements were made by the management board of Ciyun for the success of data collection.

Following the work of Davis et al. (1989) and Morris and Venkatesh (2000), we provided participants an introduction regarding mHealth services before they completing the questionnaire. Participants completed a survey that included the central variables in this study as well as demographics and control measures. We adapted commonly used measures from previous studies with the aim of promoting content validity. The measures of trust were adapted from the work of Gefen et al. (2003), and the measures for PIIT were adapted from work by Agarwal and Prasad (1998). The perceived health severity scale was adapted from the work of Johnston and Warkentin (2010). The measures for routine use intentions were adapted from work by Sundaram et al. (2007). Each item was measured on a 7-point Likert scale. The constructs and measurements of constructs are presented in Multimedia **Appendix A**.

After we developed the preliminary questionnaire, we sent it to two mHealth scholars for revision, and we also revised some questions based on the feedback from a pretest with 20 doctoral students. Finally, of 292 questionnaires, and 270 valid ones were obtained for a response rate of 92.5%. Among these participants, approximately 46% were males and 54% females. Approximately 70% of the participants were aged 20–40. About 39% of them had attended university and above. About 16.7% of the participants had chronic diseases. The demographic profile of the respondents is summarized in **Table 2**.

ANALYSIS AND RESULTS

The proposed research framework is tested by the partial least squares structural equation modeling (PLS-SEM) because this technique has several advantages. First, PLS-SEM is more appropriate than covariance-based structural equation modeling (CB-SEM) for analyzing a much more complex model and complicated interaction items (Shiau and Chau, 2016; Hair et al., 2019; Khan et al., 2019; Shiau et al., 2019). Second, compared to CB-SEM, PLS-SEM is more suitable for our study comprising more formative constructs and aiming to conduct exploratory research for theory development (Gefen et al., 2011; Shiau and Chau, 2016; Hair et al., 2019; Khan et al., 2019; Shiau et al., 2019). Accordingly, PLS-SEM is adopted for analyzing our research model. The measurement model was first examined to check its appropriateness. Subsequently, the structural model was analyzed to test the proposed hypotheses (Hair et al., 1998). The reliability, convergent validity, and discriminant validity were examined as indicators of the appropriateness of the measurement model (Fornell and Larcker, 1981). Following the work of Fornell and Larcker (1981), reliability was assessed by examining Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Furthermore, it is uncertain whether the combined effects of all these factors play a role in explaining routine use intentions. To address this, we conducted a post-hoc analysis by proposing a three-way interaction to examine the combined effects of trust, PIIT, and perceived health severity on routine use intentions. To examine the three-way interaction effect on intentions to routinely use mHealth, we conducted a t-test that validated its value.

Considering all self-reported measurement scales may lead to a common method bias that could threaten the validity of our results, we conducted an assessment of common method bias (Podsakoff et al., 2003). Following the work of Harman (1976), we did this using Harman's single factor test. The results showed that all factors explained 74.5% of the variance and the first factor accounted for 37.2% of the variance. Informed by the work of McFarlin and Sweeney (1992), we believe that common method bias is unlikely to be a serious concern in this study.

TABLE 2 | Demographic profile of the respondents.

Characteristics	Statistic	
	N	Percentage
Gender		
Male	125	46.29
Female	145	53.70
Age		
20–30 years	120	44.44
31–40 years	69	25.56
41–50 years	38	14.07
51–60 years	43	15.93
Educational Level		
Primary school	2	0.74
Secondary school	75	27.77
Pre-university	88	32.59
University	71	26.29
Postgraduate	34	12.59
Chronic disease		
Yes	45	16.66
No	225	83.33

The Measurement Model

In the measurement model, the reliability, convergent validity, and discriminant validity were examined as indicators of the appropriateness of the measurement model (Fornell and Larcker, 1981). Following the work of Fornell and Larcker (1981), reliability was assessed by examining Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE). The value of Cronbach's alpha was higher than the suggested value of 0.70, thus indicating sufficient reliability. The values of CR (0.852 to 0.920) and AVE (0.658 to 0.793) were above the threshold values of 0.70 and 0.50, respectively, (Chin, 1998). Thus, all indicators indicated acceptable construct reliability (Fornell and Larcker, 1981). The convergent validity was examined by means of assessing whether all the item loadings of each construct were above the threshold value of 0.70 suggested by Chin (1998). The results in **Table 3** indicated that the values of the loadings of all items were higher than 0.70, thereby indicating good convergent validity. The discriminant validity was found to be acceptable because the results indicated the loadings of all items were above their cross-loadings on other constructs, and the correlations of any two constructs were smaller than the square roots of the AVE of each construct. The correlations and discriminant validity of all constructs are presented in **Tables 3, 4**.

The Structural Model

The structural model was assessed by checking the significance of path coefficients (β) between various factors. The PLS results of all proposed relationships are reported in **Figure 2**. To better examine the interaction effects of these three variables on routine use intentions, we conducted a two-stage criterion in the model analysis. First, the direct effects of trust, PIIT, and perceived health severity on routine use intention were tested in Model 1. In Model 2, the interaction effects among these three variables on routine use intention were tested based on Model 1.

The PLS results for these two models are shown in **Table 5**. In Model 1, trust ($\beta = 0.518$, $t = 10.586$, $P < 0.001$), PIIT ($\beta = 0.135$, $t = 2.383$, $p = 0.008$), and perceived health severity ($\beta = 0.154$, $t = 3.971$, $P < 0.001$) were found to have significant effects on routine use intentions. Thereby, H1, H2, and H3 were supported. These three variables combined can explain 37.5% of the variance in routine use intentions. In Model 2, contrary to our hypothesis, perceived health severity was found to have a negative moderating effect on the association between trust and routine use intentions ($\beta = -0.220$, $t = 4.176$, $P < 0.001$), and hence H4 was not supported. Perceived health severity was found to have a positive moderating effect on the association between PIIT and routine use intentions ($\beta = 0.166$, $t = 3.498$, $P < 0.001$), thus supporting H5. However, PIIT had no significant moderating effect on the association between trust and routine use intention ($\beta = 0.034$, $t = 0.578$, $p = 0.280$). Therefore, H6 was not supported. With respect to the results of control variables, gender ($\beta = -0.045$, $t = 0.566$, $p = 0.285$), education ($\beta = -0.047$, $t = 0.549$, $p = 0.481$), chronic diseases ($\beta = -0.107$, $t = 1.471$,

TABLE 3 | Correlations and discriminant validity.

Construct	Mean	Standard deviation	Cronbach's alpha	Composite reliability	AVE	RUI	TRU	PIIT	PHS
RUI	5.06	1.108	0.863	0.916	0.785	**0.886**			
TRU	5.38	1.050	0.876	0.915	0.729	0.578	**0.854**		
PIIT	5.61	1.192	0.869	0.920	0.793	0.318	0.354	**0.890**	
PHS	3.80	1.830	0.745	0.852	0.658	0.197	0.081	0.018	**0.811**

AVE = Average variance extracted; RUI = Routine use intention; TRU = Trust; PIIT = Personal innovativeness in IT; PHS = Perceived health severity.

TABLE 4 | Loadings and cross-loadings for measurement items.

	Routine use intention (RUI)	Trust	Personal innovativeness (PIIT)	Perceived health severity (PHS)
RUI1	**0.880**	0.531	0.305	0.172
RUI2	**0.901**	0.514	0.282	0.187
RUI3	**0.876**	0.491	0.256	0.165
Trust1	0.489	**0.840**	0.311	−0.003
Trust2	0.463	**0.849**	0.333	0.058
Trust3	0.534	**0.878**	0.289	0.049
Trust4	0.484	0.848	0.281	0.174
PIIT1	0.280	0.334	**0.890**	0.030
PIIT2	0.277	0.333	**0.893**	0.015
PIIT3	0.291	0.281	**0.889**	0.005
PHS1	0.149	0.093	0.035	**0.828**
PHS2	0.133	0.050	−0.049	**0.824**
PHS3	0.186	0.054	0.045	**0.781**

RUI = Routine use intention; TRU = Trust; PIIT = Personal innovativeness in IT; PHS = Perceived health severity.

$p = 0.457$), and age ($\beta = 0.057$, $t = 0.753$, $p = 0.477$) had no significant effects on routine use intention regarding mHealth services. Compared with Model 1, Model 2 (42.2%) explains 4.7% more variance in routine use intentions. The results of each hypothesis are summarized in **Table 6**.

Post-hoc Analysis

Although trust, PIIT, and perceived health severity successfully explain a significant portion of the variance in routine use intentions regarding mHealth services (42.2%), the three-way interaction effects of these three factors on routine use intention remain underexplored. Therefore, we conducted a post-hoc analysis to examine the combined effects of trust, PIIT, and perceived health severity on routine use intentions.

We hypothesized that perceived health severity would influence the interaction effects of trust and PIIT on individuals' intention to routinely use mHealth. In situations of low perceived health severity and in individuals with low PIIT, trust may relate more positively to routine use intentions. This is because when the perceived seriousness of a health-related threat is low, individuals with low PIIT may rely on trust to determine their routine use intentions. Such individuals may spend time evaluating the performance of mHealth services, and they may be more likely to make rational behavioral decisions regarding mHealth. In contrast, when individuals with high PIIT perceive their health severity as high, the association between trust and routine use intention would be weaker. This is because such individuals may routinely use mHealth services regardless of the trustworthiness of those services, as they may be more willing to engage in security behavior to reduce the seriousness of the health-related threat. Therefore, they are more likely to make irrational behavioral decisions regarding mHealth services. This supposition is supported by previous studies (Prentice-Dunn and Rogers, 1986; Rai et al., 2013; Zhao et al., 2017). The three-way interaction of trust, PIIT, and perceived health severity had a statistically significant positive effect on implementation ($\beta = 0.139$, $t = 3.047$, $p < 0.01$) and explained 44.2% of the variance in intentions to routinely use mHealth.

DISCUSSION AND IMPLICATIONS

Key Findings

There are three key findings from this study. First, consistent with previous studies on mHealth services (Rai et al., 2013; Zhao et al., 2017), we found that both trust and PIIT positively influence routine use intentions. Furthermore, we found that trust has primary explanatory power over PIIT. This affirms the value of trust theory, in which the health information asymmetry between health professionals and normal users helps to explain the adoption and use of mHealth services. Additionally, perceived health severity has a positive impact on routine use intentions. This shows that when users believe that they are more likely to suffer harm from a serious disease, they will tend to use mHealth services routinely to avoid or reduce the threat. This finding is also supported by prior studies (Sun et al., 2013; Guo et al., 2015).

Second, perceived health severity weakens the effects of trust but strengthens the effects of PIIT on routine use intention. **Figure 3**, which shows the effects of trust, reflects a large difference in routine use intention under low perceived health severity ($\mathrm{RUI}_{\mathrm{low}}^{\mathrm{trust}} = 2.144$ vs. $\boldsymbol{RUI}_{\boldsymbol{high}}^{\boldsymbol{trust}} = 3.570$) and a relatively small difference under high perceived health severity ($\mathrm{RUI}_{\mathrm{low}}^{\mathrm{trust}} = 2.900$ vs. $\boldsymbol{RUI}_{\boldsymbol{high}}^{\boldsymbol{trust}} = 3.386$). However, **Figure 4**, which shows the effects of PIIT, indicates a large difference in routine use intention under high perceived health severity ($\mathrm{RUI}_{\mathrm{low}}^{\mathrm{PIIT}} = 2.809$ vs. $\mathrm{RUI}_{\mathrm{high}}^{\mathrm{PIIT}} = 3.477$) and a relatively small difference under low perceived health severity ($\mathrm{RUI}_{\mathrm{low}}^{\mathrm{PIIT}} = 2.865$ vs. $\mathrm{RUI}_{\mathrm{high}}^{\mathrm{PIIT}} = 2.849$). These results indicate that when perceived health severity is at a higher level, PIIT plays a more significant role than trust in enhancing routine use intention. Moreover, the interaction effect between trust and perceived health severity on routine use intention is significant but negative, which is inconsistent with hypothesis 4. This controversial result could be explained by the basic tenet of protection motivation theory (Rogers, 1975). In other words, a higher level of perceived health severity will make individuals feel more anxious about their health conditions and unsafe in the face of the significant threat. Therefore, individuals with higher health severity will try out any new health-related technology (e.g., mHealth services), regardless of its trustworthiness, that can prevent or reduce the threat.

Third, we found that a three-way interaction of trust, PIIT, and perceived health severity affected routine use intention of mHealth services. This indicates that when individuals perceive health severity as low, trust plays a more important role than PIIT in predicting routine use intention. Under the condition of low severity, users tend to make rational health-related decisions. In contrast, when individuals perceive their health severity as high, those with high PIIT will actively engage in routine use of mHealth services even when this innovation is not trustworthy. In this situation, users tend to make irrational health-related decisions.

TABLE 5 | The results of the structural equation model (SEM).

Path	Model 1	Model 2
TRU → RUI	0.518***	0.484***
PIIT→RUI	0.135**	0.172***
PHS → RUI	0.154***	0.140***
TRU*PHS → RUI		−0.220***
PIIT*PHS → RUI		0.166***
TRU*PIIT→RUI		0.034^{ns}
R^2	0.375	0.422
R^2 Change		0.047

RUI, Routine use intention, TRU, Trust, PIIT, Personal innovativeness in IT, PHS, Perceived health severity. ***$p<0.001$; **$p<0.01$; *and ns, not significant.*

Theoretical and Practical Implications

This study can contribute to the mHealth literature in several ways. First, we are one of the first to propose a person–technology–health (PTH) research framework to facilitate a comprehensive understanding of the routine use of mHealth services. Consistent with previous studies (Deng et al., 2015;

TABLE 6 | Summary of Results.

Hypothesis description	Result
H1: Trust increases individuals' routine use intentions regarding mHealth services	Supported
H2: PIIT increases individuals' routine use intentions regarding mHealth services	Supported
H3: Perceived health severity increases individuals' routine use intentions regarding mHealth services	Supported
H4: Perceived health severity has a positive moderating impact on the association between trust and individuals' routine use intentions regarding mHealth services	Not supported
H5: Perceived health severity has a positive moderating impact on the association between PIIT and individuals' routine use intentions regarding mHealth services	Supported
H6: PIIT has a positive moderating impact on the association between trust and individuals' routine use intentions regarding mHealth services	Not supported

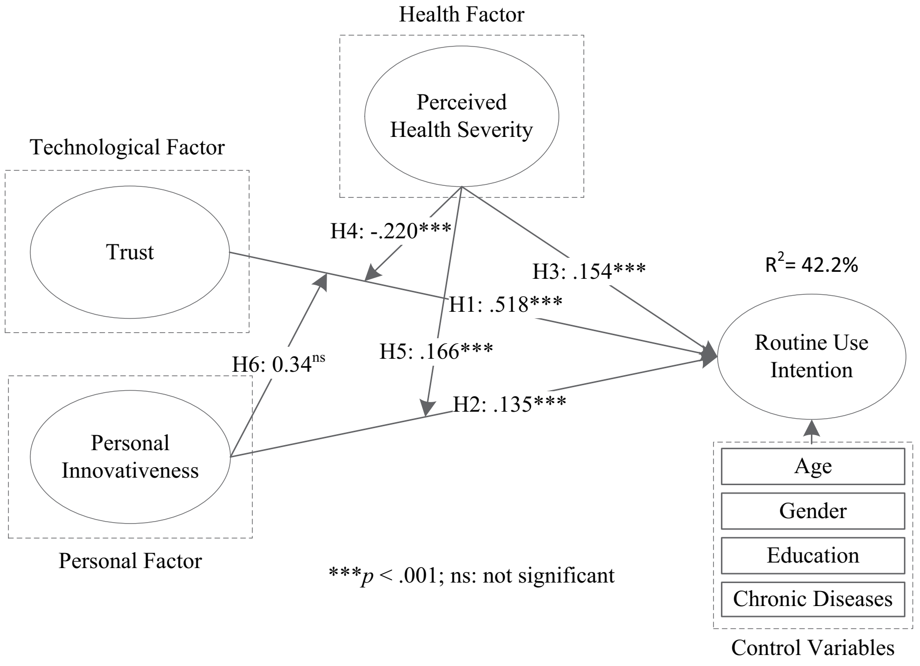

FIGURE 2 | PLS results.

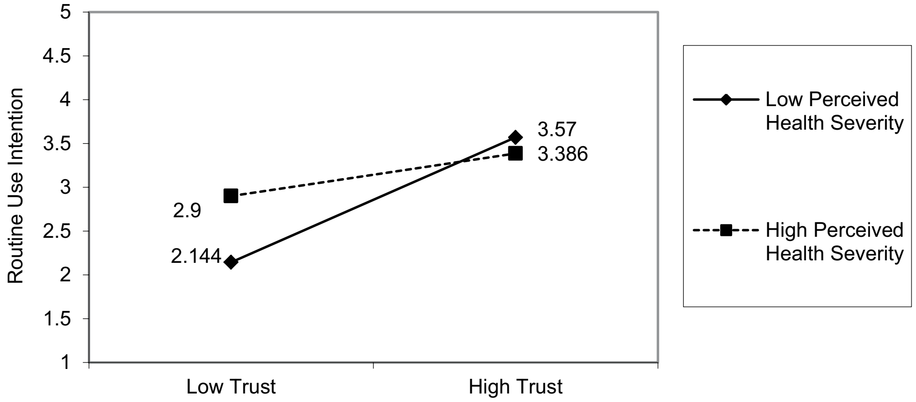

FIGURE 3 | Effects of perceived health severity on the relationship between trust and routine use intention.

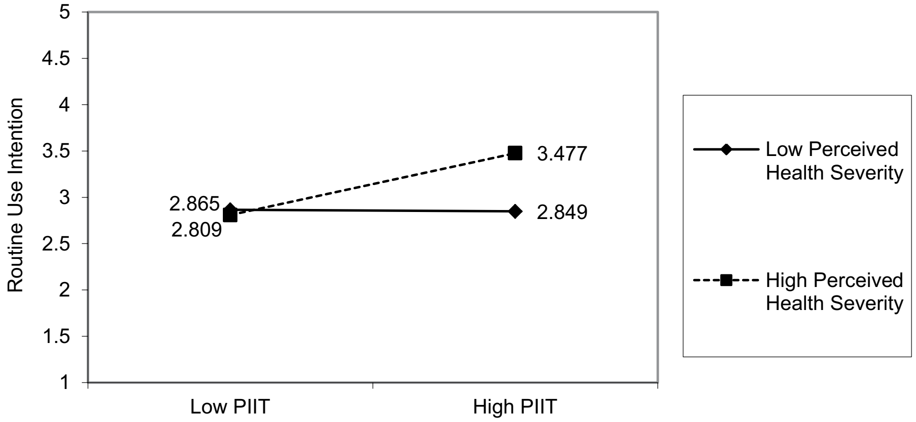

FIGURE 4 | Effects of perceived health severity on the relationship between PIIT and routine use intention.

Zhao et al., 2017; Zhang et al., 2020; Meng et al., 2021), the findings confirm the significant roles of technological factors, personal factors, and health factors in predicting mHealth service adoption and use in general and routine use in particular. More importantly, although prior studies have examined the two-way interaction effect of personal, technological, and health factors on mHealth adoption and use (Deng et al., 2015; Chen et al., 2018; Meng et al., 2019b; Alam et al., 2020), this study, for the first time, tested the three-way interaction effect of aforementioned factors. The findings shed light on the role of personal factors and health factors in influencing the effects of technological factors to various degrees. Therefore, this PTH research framework can address interaction effects in a way that complements traditional adoption theory. Our PTH framework can be adapted by future researchers investigating the adoption and use of specific health IT, such as mHealth services.

Second, this study highlights the difference between mHealth services and other IT by investigating the role of health factors. In contrast to most previous studies focusing solely on the effects of technological factors and personal factors (Hoque and Sorwar, 2017; Chen et al., 2018), this study extends prior research by introducing the role of health factors and exploring the combined effects of technological factors, personal factors, and health factors. Considering the fact that using mHealth services is seen as not only an ordinary IT use behavior but also a health-relevant behavior, this study can provide novel insight into mHealth adoption and usage through illuminating the moderating effect of health factors (e.g., perceived health severity) on technological factors and personal factors. For example, users' rational or irrational decision-making processes regarding routine mHealth use are to some extent determined by perceived health severity. By taking advantage of such health factors, future studies could shed yield more interesting findings.

Several practical implications can also be derived from the study. First, trust, PIIT, and perceived health severity are found to be significant in promoting users' routine use intentions of mHealth services. This implies that mHealth service providers should not only develop relevant strategies to improve their services' technological factors (e.g., trustworthiness, perceived usefulness, and perceived ease of use), but they also need to pay more attention to their targeting users' personal factors and health factors. Such attention would allow developers to comprehensively understand the antecedents of routine use intentions and focus service development in a way that increases the likelihood of routine use.

Second, our study indicates that perceived health severity has a negative impact on the positive relationship between trust and routine use intention but strengthens the positive relationship between PIIT and routine use intention. Although technological factors (e.g., trust) and personal factors (e.g., PIIT) are critical predictors of routine use intention related to mHealth services, their impacts will be moderated to various degrees in the presence of health factors. With this understanding, providers may be motivated to acquire users' personal health-related data (e.g., health records, disease history, family heredity history, and disease types). Such data acquisition would aim to differentiate consumers who may face the same health-relevant threat but at different levels, which would allow developers to adopt more user-centric strategies based on users' health factors, thus increasing users' routine use and sustaining the company's development. Overall, the findings of this study could benefit providers of mHealth services by providing the PTH framework, which would allow providers to comprehensively understand how users' personal traits influence the way they evaluate mHealth services when they are threatened with a health condition.

Limitations

Our research has several limitations. First, as our representatives of technological, personal, and health factors, we only choose trust, PIIT, and perceived health severity. Other factors may generate more interesting results and increase the explanatory power of the PTH framework. Second, since we collected data in China, the generalizability of this study to other cultural contexts is limited. In western countries, for instance, mHealth users may exhibit different levels of PIIT and perceived health severity. Future studies should validate the research model in other cultural contexts to ensure the validity of the findings. Third, while our study uses a cross-sectional design, which is limited in its ability to draw causal inferences, future researchers could erase this limitation by using a longitudinal design.

CONCLUSION

This study proposes the PTH framework as a way to understand users' routine use of mHealth services by exploring how technological factors (e.g., trust), personal factors (e.g., PIIT), and health factors (e.g., perceived health severity) combine to influence routine use intention. This synthesized PTH research framework provides a greater understanding of the complex and dynamic interactions that influence routine use intentions of mHealth users. Our results show that routine use intentions are significantly associated with trust, PIIT, and perceived health severity, as three components of the PTH framework. Specifically, we found that trust has much more explanatory power than PIIT and perceived health severity. In situations of low perceived health severity, trust will increase the routine use intention of users with low PIIT rather than those with high PIIT. In situations of high perceived health severity, trust plays a less important role in predicting routine use intention for individuals with high rather than low PIIT. The extant literature on mHealth services has provided limited knowledge that is related to the combined effects of technological factors, personal factors, and health factors. Thus, our study not only extends the existing mHealth literature but also provides significant practical implications for providers of mHealth services.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation. Queries and requests to access materials should be directed to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Harbin Institute of Technology School of Management. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

FM: conceptualization, methodology, and writing—original draft. XG: conceptualization, and writing—review and editing. ZP: methodology and writing—original draft. XZ: writing—review and editing. K-hL: writing—review and editing, and supervision. All authors contributed to the article and approved the submitted version.

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APPENDIX A

Research Constructs and Items

Routine Use Intention: (Sundaram et al., 2007)

RUI 1. I predict I will incorporate mHealth services into my regular life schedule.
RUI 2. mHealth services will be pretty much integrated as part of my normal life routine.
RUI 3. mHealth services will be a normal part of my life.

Trust: (Gefen et al., 2003)

PU1. I know that mHealth services are honest.
PU2. I know that mHealth services care about their customers.
PU3. I know that mHealth services are not opportunistic.
PU4. I know that mHealth services are predictable.

Personal Innovativeness in Information Technology: (Agarwal and Prasad, 1998)

PIIT1. I am willing to try new information technologies.
PIIT2. I think it is very interesting to try new information technologies.
PIIT3. I enjoy trying new information technologies.

Perceived Health Severity: (Johnston and Warkentin, 2010)

PHS1. If I were affected by a disease, it would be severe.
PHS2. If I were affected by a disease, it would be serious.
PHS3. If I were affected by a disease, it would be significant.

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Appsolutely secure? Psychometric properties of the German version of an app information privacy concerns measure during COVID-19

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Introduction: Privacy concerns are an important barrier to adoption and continued use of digital technologies, particularly in the health sector. With the introduction of mobile health applications (mHealth apps), the construct of app information privacy concerns has received increased attention. However, few validated measures exist to capture said concerns in population samples, although they can help to improve public health efforts.

Methods: Using a cross-sectional survey of German adults (mean age = 35.62; 63.5% female), this study examined psychometric properties of the app information privacy concerns scale (AIPC). Analyses comprised confirmatory factor analysis, factorial validity (exploratory factor analysis), internal consistency, convergent validity (i.e., correlations with privacy victimhood, and app privacy concerns), and discriminant validity (i.e., daily app use, adoption intentions, and attitudes toward COVID-19 contact tracing app use).

Results: The analysis did not support the proposed three-factor structure of the AIPC (i.e., anxiety, personal attitude, and requirements). Instead, a four-factor model was preferable that differentiated requirements regarding disclosure policies, and personal control. In addition, factors mirroring anxiety and personal attitude were extracted, but shared a significant overlap. However, these factors showed good reliability, convergent and discriminant validity.

Discussion: The findings underline the role of app information privacy concerns as a significant barrier to mHealth app use. In this context, anxiety and personal attitudes seemed particularly relevant, which has implications for health communication. Moreover, the observed differentiation of external (disclosure) and internal (control) requirements aligns with health behavior change models and thus is a promising area for future research.

KEYWORDS

privacy concerns, mHealth, assessment, COVID-19, validation, apps, cross-sectional, contact tracing

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Introduction

Today, ubiquitous computing is a reality, and smart mobile devices enable us to work, communicate and interact everywhere (Abowd and Mynatt, 2000; Friedewald and Raabe, 2011). Mobile applications or apps as technological interfaces for end-users fulfill different functions, and offer a variety of possibilities: organizing apps (e.g., calendars, to-do-lists), informational and communication apps (e.g., news channels, WhatsApp), entertainment apps (e.g., mobile games), and mixed apps (e.g., educational games, social media apps with organizing functions) are some examples (e.g., Hew et al., 2015). Their popularity and reach have led to increased interest in mobile health (*mHealt*h) in recent years, with apps addressing prevention (e.g., supporting a healthy diet), treatment (e.g., monitoring medication adherence), and recovery (e.g., providing tips for physical activity following surgery). MHealth apps comprise self-administered apps but also monitoring apps, and diagnostic tools to support medical decisions, and the translation of treatment effects into everyday life (e.g., Martínez-Pérez et al., 2014; Byambasuren et al., 2018; Chib and Lin, 2018; Hensher et al., 2021; Grundy, 2022).

In Germany, since late 2019, new legislation (so-called *Digitale Versorgung Gesetz*) allows medical professionals to prescribe mHealth apps as medical devices (e.g., for depressive disorders, or to monitor blood pressure). While this approach to public health and personalized medicine is commendable (Grundy, 2022), it also leads to questions about data security, privacy, and commercialization of health (Martínez-Pérez et al., 2014). In fact, many apps gather (sensitive) personal data, and the more data, the more precise the customization to individual needs, which supports successful treatment processes. Hence, highly customizable apps require a trade-off between information privacy and comfort or customization (Jeminiwa et al., 2019; Iwaya et al., 2020; Hensher et al., 2021; Grundy, 2022). Information privacy refers to the degree of autonomous and self-directed disclosure of private information (Smith et al., 2011). App-based data therefore has a high economic value and needs far-reaching protection. From a user-centered design perspective, establishing transparent privacy policies and data security measures is paramount (Azhar and Dhillon, 2016; Adjekum et al., 2018; Jeminiwa et al., 2019). Moreover, from an end-user perspective, it is important to trust data security protocols, and a lack of trust can impede uptake and continued use of digital health technologies, such as apps (Schnall et al., 2015; Azhar and Dhillon, 2016). Frameworks like the unified theory of acceptance and use of technology (UTAUT; e.g., Venkatesh and Davis, 2000; Venkatesh et al., 2003, 2012) have adopted issues like privacy concerns and lack of trust in technologies as perceived barriers of use. Consequently, many studies using the UTAUT framework have also examined these constructs (Williams et al., 2015; Dwivedi et al., 2020).

Literature review of information privacy measures in mobile applications

Although the literature on information privacy and data security provides a variety of measures and constructs to measure end-user attitudes, few instruments focus on apps (Bélanger and Crossler, 2011; Li, 2011; Dinev et al., 2015; Benjumea et al., 2020). So far, many studies have analyzed privacy policies of app providers, reviewed or suggested measures or content of data security statements and policies. However, real-world evaluations of these suggestions are scarce (e.g., Li, 2011; Sunyaev et al., 2015; Chib and Lin, 2018; Benjumea et al., 2020; Iwaya et al., 2020; Grundy, 2022). Consequently, studies should focus on user perceptions of information privacy. Previous research has produced instruments measuring general concern for information privacy in the population, in internet users, and in mobile users (Bélanger and Crossler, 2011; Li, 2011). These measures usually capture attitudes toward data collection, storage, and surveillance, perceived personal control, and (fear of) secondary use of information. So far, only one measure, the app information privacy concern scale (AIPC) includes all of these aspects regarding mobile applications (Buck and Burster, 2017). It synthesizes previous work on Concerns for Information Privacy (Smith et al., 1996), Internet Users' Information Privacy Concerns (Malhotra et al., 2004), and Mobile Users' Information Privacy Concerns (Xu et al., 2012). Buck and Burster (2017) developed the measure in a three-step process: They started with items from Internet Users' Information Privacy Concerns measure (Malhotra et al., 2004), which was based on Concerns for Information Privacy (Smith et al., 1996). The measure describes collection (i.e., concern about an imbalance of costs and benefits regarding data sharing *via* services), control (i.e., perceived control over personal information and data use), and awareness (i.e., awareness about organizational information privacy practices). Then, they extended the model by including Mobile Users' Information Privacy Concerns (Xu et al., 2012), specifically, concerns about perceived surveillance, intrusion, and secondary use of information. In a third step, they added an item measuring general information privacy concerns (I am concerned about threats to my personal privacy today) based on Smith et al. (1996). Their analysis of the instrument resulted in a three-factor model with the factors anxiety (factor 1), personal attitude (factor 2), and requirements (factor 3). Anxiety describes concerns regarding collection, secondary use of data, and surveillance. Personal attitude refers to preferences regarding information and disclosure, and requirements refer to request toward third parties about data handling.

To date, though, the scale has not been validated in other samples and applied contexts. Hence, this study presents a validation of the German version of the AIPC in a community sample. As context, this study addresses the use of a Corona virus tracing app (e.g., the Corona Warn-App) as a use case of app information privacy. Contact tracing apps are technological solutions that support infection prevention and public health efforts, and more than 100 countries use(d) contact tracing apps during the COVID-19 pandemic (Gupta et al., 2021). Contact tracing apps require users to agree to surveillance and contact tracing *via* their smart device. The apps inform users about contact with positive (infected) cases, suggest adequate preventive and mitigation measures, and allow governmental institutions to define containment or hotspot zones (Kahnbach et al., 2021). Previous studies examined barriers and facilitators of adopting tracing app use and showed that they are effective in reducing infection rates (e.g., Jenniskens et al., 2021; Kahnbach et al., 2021; Kolasa et al., 2021). However, tracing apps often do not provide sufficient information about personal data breaches, which might increase privacy concerns and subsequently, reduce use intentions (Jenniskens et al., 2021). Hence, contact tracing apps are an important use case to investigate privacy concerns regarding mobile health apps. Therefore, this study examines psychometric properties of the German version of the AIPC in the context of the COVID-19 pandemic.

Materials and methods

Between May and July 2020, data was collected *via* an online survey on adopting a COVID-19 tracing app. Recruitment efforts comprised social media posts (Facebook groups, corona-related websites, YouTube), press outlets (local news report, Press, and Media Relations Office of the University), and personal communications. The survey was pretested *via* cognitive debriefings of a small sample ($n = 20$) to ensure clarity, readability, accessibility, and proper functioning. During the pretest, participations took between 10 and 60 min to complete the survey (depending on literacy, familiarity with surveys, etc.). Therefore, a time frame of 10–60 min was defined as a rule of thumb to identify outliers. The survey captured a period of about 4 weeks before and after the launch of the governmentally supported COVID-19 tracing app, the Corona Warn-App (June 16). The survey comprised questions about adoption intentions, motivations and barriers of tracing app use, including information privacy concerns. While a previous study (Tomczyk et al., 2021) focused on predictors of and barriers to tracing app use (with privacy concerns as one of many variables), this study inspects psychometric properties of the AIPC scale to assess its utility for the field. As a frame of reference for contact tracing apps, we described the functionality of contact tracing apps as (i) monitoring and tracking infection chains, (ii) delivering immediate support and information in case of an infection or contact with an infected person, and (iii) and possibly, providing support for persons in quarantine by monitoring health, and tailoring information and preventive actions.

Sample

In sum, 593 persons took part in the survey. After excluding speeders, that is participants who completed the survey in less than 10 min or showed monotone response patterns for $>80\%$ of the questions, 349 participants remained (mean age = 35.62, SD = 14.66; range = 18–82 years; 63.5% female). On average, participants completed the survey in 22.65 (SD = 7.93) minutes. Participants could enter a raffle to win one of fifty gift vouchers (€15 each) as an incentive. Having completed the study, participants received additional information on COVID-19 and tracing apps, including several hyperlinks to freely available tracing apps. The local Ethics Committee approved the study procedure. Items of the survey are accessible as **Supplementary Material** of a previous publication (Tomczyk et al., 2021).

Measurement instruments

Sociodemographic data

Sociodemographic data comprised age, gender [1 (female), 2 (male)], number of persons in one's household, current level of education [1 (upper secondary education, i.e., "Abitur" or higher educational achievement), 0 (lower secondary education or less)], region [0 (rural, i.e., up to 10,000 inhabitants), 1 (urban, i.e., up to 100,000 inhabitants), 2 (metropolitan, i.e., over 100,000 inhabitants); dummy-coded with rural as a reference category)], and migration background [1 (father/mother/participant born in Germany), 2 (father/mother/participant born elsewhere)].

App information privacy concerns

The AIPC scale (German version of the scale provided *via* personal communication; Buck and Burster, 2017) comprises seventeen items (α = 0.91), for instance, "A good privacy policy for mobile app users should have a clear and conspicuous disclosure" (see **Table 1**). The response scale is a seven-point Likert scale. For the analysis, we performed a confirmatory factor analysis of the three factors suggested by Buck and Burster (2017). However, we also tested factorial validity of the AIPC *via* an exploratory factor analysis. We used mean values of relevant subscales for statistical comparisons. Although it is recommended to perform exploratory and confirmatory factor analysis in different samples (Hurley et al., 1997), this study aims to examine psychometric properties of the original scale developed by Buck and Burster (2017). Given the differences in sample composition, both analyses are included to illustrate the impact of these differences and inform future research.

Convergent validity measures

To test convergent validity, direct and indirect experiences of privacy victimhood and data misuse were measured on a five-item scale (α = 0.91; e.g., How frequently have you personally been the victim of what you felt was an improper invasion of privacy?). Items were rated on a five-point Likert scale from 0 (never) to 5 (very frequently) and based on previous research on information privacy concerns (Xu et al., 2012). Furthermore, an open-ended question asked participants why they might not use a contact tracing app. Responses were coded to reflect tracing app privacy concerns [1 (yes), 0 (no)] as a reason for non-use.

Discriminant validity measures

Discriminant validity measures included daily app use, adoption intentions, and attitudes toward COVID-19 tracing apps. Intentions comprised a scale of three items [e.g., I plan to use a tracing app within the next 3 months; 1 (highly unlikely) to 7 (highly likely); ($\alpha = 0.99$)]. Attitudes were measured *via* a four-item scale (e.g., good-bad, helpful–not helpful) on a 7-point semantic differential, recoded to represent positive attitudes ($\alpha = 0.89$). An open-ended question captured daily smartphone app use (in hours).

Statistical analysis

First, descriptive statistics of sociodemographic and attitudinal data were inspected. Second, a confirmatory factor analysis tested the three-factor model proposed by Buck and Burster (2017). Model fit indices (Chi Square test, CFI, TLI, and RMSEA; Schreiber et al., 2006) are reported. A non-significant Chi Square test ($p > 0.05$), CFI greater than 0.95, TLI greater than 0.90, and RMSEA lower than 0.08 indicate good model fit (Schreiber et al., 2006). Third, an exploratory factor analysis of the AIPC using varimax rotation, with a KMO > 0.70 as quality indicator (Dziuban and Shirkey, 1974) was performed to test factorial validity. Fourth, reliability was tested *via* internal consistency (Cronbach's α) for the AIPC and the subscales. Fifth, for convergent and discriminant validity, correlations of AIPC values with experiences of privacy victimhood and app privacy concerns (convergent validity) as well as daily app use, intentions, and attitudes toward tracing app use (discriminant validity) were examined. Descriptive statistics and correlations were calculated with SPSS version 27 (RRID: SCR_016479), factor analyses with Mplus version 8 (Muthén and Muthén, 1998-2017, RRID: SCR_015578). All analyses assumed $\alpha = 0.05$.

Results

Descriptive statistics

The sample consisted of 349 participants (M_{age} = 35.62 years; 65.3% female) with mostly higher secondary education, from urban or metropolitan regions, and without a migration background (77.4%). Overall, app information privacy concerns were rather high, yet a minority ($n = 30$; 8.6%) explicitly stated privacy concerns as a main reason for non-use of the contact tracing app (see **Table 2**).

Confirmatory factor analysis

The confirmatory factor analysis showed a poor fit of the three-factor model [$\chi^2 = 722.66$, $df = 116$, $p = < 0.001$; CFI = 0.84, TLI = 0.81, and RMSEA = 0.12, 90% CI (0.11,0.13)].

TABLE 1 Items of the app information privacy concerns scale.

Item	Text
1	I am concerned that mobile apps are collecting too much information about me.
2	I believe that as a result of my using mobile apps, information about me that I consider private is now more readily available to others than I would want.
3	I am concerned that mobile apps may monitor my activities on my mobile device.
4	I feel that as a result of my using mobile apps, information about me is out there that, if used, will invade my privacy.
5	I am concerned that mobile apps may use my personal information for other purposes without notifying me or getting my authorization.
6	I am concerned that mobile apps may share my personal information with other entities without getting my authorization.
7	When I give personal information to use mobile apps, I am concerned that apps may use my information for other purposes.
8	I am concerned about threats to my personal privacy today.
9	It is very important to me that I am aware and knowledgeable about how my personal information will be used.
10	When mobile apps ask me for personal information, I sometimes think twice before providing it.
11	To me, it is the most important thing to keep my privacy intact from app providers.
12	Compared to others, I am more sensitive about the way mobile app providers handle my personal information.
13	A good privacy policy for mobile app users should have a clear and conspicuous disclosure.
14	Mobile app providers seeking information online should disclose the way the data are collected, processed, and used.
15	(Mobile app user) control of personal information lies at the heart of mobile app users' privacy.
16	Mobile app privacy is really a matter of consumers' right to exercise control and autonomy over decisions about how their information is collected, used, and shared.
17	It usually bothers me when mobile apps ask me for personal information.

TABLE 2 Descriptive statistics of sociodemographic data and attitudinal variables in the analysis sample (N = 349).

	Total (N = 349) [n (%) or mean (SD)]
Sociodemographic data	
Age (range: 18–82)	35.62 (14.66)
Gender (female)	226 (65.30)
Persons per household	2.53 (1.58)
Education	
≤Lower secondary	55 (16.50)
Upper secondary	278 (83.50)
Region	
Rural	66 (20.10)
Urban	143 (43.60)
Metropolitan	119 (36.30)
Migration background[a]	79 (22.60)
Attitudinal variables	
App information privacy concerns (range: 1–7)	
Anxiety	5.55 (1.12)
Personal attitudes	5.52 (1.12)
Requirements	6.12 (0.70)
Privacy victimhood (range: 1–5)	2.33 (0.83)
Privacy concerns (yes, as a barrier to tracing app use)	30 (8.60)
Adoption intentions of tracing app use (range: 1–7)	3.66 (2.37)
Attitudes toward tracing app use (range: 1–7)	4.19 (1.65)
Daily smartphone app use (hours per day)	2.63 (1.78)

[a] Either the respondent, their mother or their father were not born in Germany.

In this model (see **Supplementary Table 1**), standardized factor loadings were acceptable [(i.e., above 0.5) for factor 1 (anxiety), and factor 2 (personal attitudes)]. However, factor loadings were low for items 15 (β = 0.245), 16 (β = 0.274), and 17 (β = 0.350), which were part of factor 3 (requirements). Interestingly, item 17 (It usually bothers me when mobile apps ask me for personal information) also showed poor fit in the original analysis by Buck and Burster (2017).

Exploratory factor analysis

The exploratory factor analysis with varimax rotation showed a good fit of the data (KMO = 0.90), and explained about 59.8% of cumulative variance. However, not three but four factors reached an eigenvalue > 1 (see **Table 3**), which was confirmed by parallel analysis (with 10 replications). Except for one item, all items had a loading of >0.53 on at least one factor. Factor 3 (disclosure; 5.2% explained variance) and 4 (control; 4.6%) were distinct, but factor 1 (information; 41.7%) and 2 (data misuse; 8.3%) shared variance in items referring to the collection of personal data (item 1) as well as the concern about the misuse of information (items 5 to 7). According to the analysis, factor 1 comprised eight items, factor 2 five items, factor 3 and 4 two items each.

Compared to the original analysis by Buck and Burster (2017), factor 2 overlapped with the factor labeled *anxiety*, while factor 1 included all items of the factor named *personal attitude,* but also shared variance with items from factor 2. The original factor titled *requirements* was split in two: requirements regarding disclosure (factor 3) and control (factor 4).

Internal consistency

The three-factor model showed very good (factor 1/anxiety: α = 0.91), good (factor 2/personal attitude: α = 0.82), and poor internal consistency (factor 3/requirements: α = 0.59). The four-factor model showed acceptable, (factor 4/control: α = 0.76; factor 2/data misuse: α = 0.79), good (factor 3/disclosure: α = 0.81), and very good internal consistency (factor 1/information: α = 0.92).

Convergent and discriminant validity

Results of convergent and discriminant validity of the three-factor model and the four-factor model of app information privacy concerns are presented in **Table 4**. AIPC scores of the three-factor model correlated positively with privacy victimhood [$r(347) = 0.36$, $p < 0.001$] and negatively with daily app use [$r(347) = -0.13$, $p = 0.020$], adoption intentions [$r(347) = -0.30$, $p < 0.001$], and attitudes [$r(347) = -0.36$, $p < 0.001$]. The correlation with privacy concerns was not significant [$r(347) = -0.01$, $p = 0.836$]. In fact, privacy concerns correlated negatively only with attitudes [$r(347) = -0.11$, $p = 0.046$], the remaining associations were not significant. Concerning the four-factor model, factor 1 (information) and factor 2 (data misuse) showed similar convergent and discriminant validity compared to the three-factor model, but factor 3 (disclosure) and factor 4 (control) did not significantly correlate with any other variable.

Discussion

This study examined the psychometric properties of the German version of the AIPC scale (Buck and Burster, 2017) in an online survey on COVID-19 contact tracing apps. The analysis included a confirmatory and exploratory factor analysis of the scale (factorial validity), tests of internal consistency (reliability), and correlations with barriers (convergent validity) and facilitators (discriminant validity) of contact tracing app use.

Overall, the study did not fully support the proposed three-factor structure of the scale. While the analyses mostly

TABLE 3 Results of the exploratory factor analysis with varimax rotation of the app information privacy concerns scale (N = 349).

	Factor 1 ("information")	Factor 2 ("data misuse")	Factor 3 ("disclosure")	Factor 4 ("control")
Item 1	*0.608*	**0.626**	0.181	−0.055
Item 2	0.160	**0.687**	0.102	0.204
Item 3	**0.646**	*0.487*	0.140	0.041
Item 4	0.145	**0.710**	0.081	0.140
Item 5	*0.548*	**0.591**	0.318	−0.158
Item 6	*0.533*	**0.543**	0.337	−0.139
Item 7	**0.593**	*0.591*	0.264	−0.146
Item 8	**0.539**	0.341	0.078	−0.048
Item 9	**0.587**	0.148	0.402	0.160
Item 10	**0.582**	0.108	0.102	0.071
Item 11	**0.825**	0.111	0.181	0.076
Item 12	**0.716**	0.181	0.087	0.091
Item 13	0.184	0.113	**0.793**	0.122
Item 14	0.240	0.242	**0.719**	0.194
Item 15	0.063	0.099	0.066	**0.735**
Item 16	0.019	0.016	0.149	**0.719**
Item 17	**0.369**	0.271	0.156	−0.006
Explained variance	41.747	8.313	5.229	4.559
Eigenvalue (sample correlation matrix)	7.448	1.824	1.314	1.144
Eigenvalue (parallel analysis)	1.405	1.321	1.221	1.205

Highest factor loadings per item are printed **in bold type**; variables with high factor loadings on two separate factors are printed *in italic type*.

TABLE 4 Bivariate correlations between app information privacy concerns, daily app use, privacy concerns as a barrier to tracing app use, privacy victimhood, adoption intentions, and attitudes toward COVID-19 contact tracing apps (N = 349).

	1	2	3	4	5	6	7	8	9	10	11	12
1. Anxiety	1											
2. Personal attitudes	0.68^{c}	1										
3. Requirements	0.40^{c}	0.44^{c}	1									
4. Information	0.66^{c}	0.93^{c}	0.28^{c}	1								
5. Data misuse	0.80^{c}	0.19^{c}	0.25^{c}	0.14^{b}	1							
6. Disclosure	0.27^{c}	0.26^{c}	0.55^{c}	0.08	0.06	1						
7. Control	−0.04	14^{b}	0.73^{c}	−0.01	−0.02	0.06	1					
8. Privacy victimhood	0.40^{c}	0.32^{c}	0.06	0.33^{c}	0.28^{c}	−0.03	−0.04	1				
9. Privacy concerns	−0.04	0.03	0.03	0.01	−0.06	0.03	0.05	0.03	1			
10. Daily app use (hours)	−0.11	−0.20^{c}	−0.01	−0.22^{c}	0.01	0.03	0.03	−0.09	0.05	1		
11. Adoption intentions	−0.33^{c}	−0.26^{c}	−0.05	−0.29^{c}	−0.24^{c}	0.03	0.10	−0.18^{c}	−0.07	0.10	1	
12. Attitudes	−0.35^{c}	−0.38^{c}	−0.11^{a}	−0.39^{c}	−0.18^{c}	−0.02	0.06	−0.24^{c}	−0.11^{a}	0.06	0.66^{c}	1

$^{a}p < 0.05$, $^{b}p < 0.01$, and $^{c}p < 0.001$.

supported the factors titled *anxiety* and *personal attitude*, they did not replicate the factor titled *requirements*. Instead, the exploratory factor analysis pointed to two distinct factors of requirements concerning disclosure and control. Although the model suggested an overlap between aspects of anxiety and personal attitude, the latter two factors of requirements were independent. In their initial development of the scale, Buck and Burster (2017) cited Concerns for Information Privacy (Smith et al., 1996), Internet Users' Information Privacy Concerns (Malhotra et al., 2004), and Mobile Users' Information Privacy Concerns (Xu et al., 2012) as important groundwork. These models describe a variety of concerns regarding the collection, storage, use and secondary use of personal data as well as expectations and values of personal control, surveillance, and awareness of privacy practices. The AIPC synthesizes prior research and applies it to mobile app use, thus providing an important step in mHealth and health IT privacy development. The analysis resulted in the three factors of AIPC, namely anxiety, personal attitude, and requirements.

However, according to the exploratory factor analysis, a four-factor model was preferable, although this model requires further validation. In this model, factor 1 (information) was similar to personal attitude, which described the perceived importance of data protection and information privacy. Yet, it was also associated with anxiety (i.e., concerns about data use, processing, and storage) and factor 2 (data misuse) in this study, respectively. Possibly, the context of contact tracing apps might have introduced this association, because it connects health-related anxiety and privacy concerns (e.g., Gupta et al., 2021; Jenniskens et al., 2021; Kahnbach et al., 2021; Kolasa et al., 2021; Tomczyk et al., 2021; Grundy, 2022). The authors did not develop the AIPC as a health-specific measure of privacy concerns, thus factors like specific health concerns (e.g., Rosenstock, 1974; Rogers, 1975) were not included. In health behavior models, such as the protection motivation theory (Rogers, 1975) or the health belief model (Rosenstock, 1974), health-related concerns and risk perceptions have a longstanding tradition. According to these models, higher risk perception can lead to higher protection motivation and more protective behavior, for instance tracing app use (as a measure of infection prevention; Tomczyk et al., 2021). In the digital age, health concerns surpass physical or psychological health and also comprises digital health; hence, mobile health apps have to fulfill general privacy requirements but also health-related privacy requirements, particularly for vulnerable populations (e.g., Grundy, 2022). With COVID-19 being a genuine threat to the global population, health-related concerns might have conflated app-related privacy concerns and thus biased assessments of anxiety and personal attitudes. Nevertheless, the negative associations with adoption intentions and attitudes underline the importance of tailored health communication to address these aspects specifically when introducing mHealth apps and digitally supported infection prevention (Adjekum et al., 2018; Kahnbach et al., 2021).

Linking privacy concerns and health behavior modeling, it also seems important to discern requirements regarding disclosure and control (as observed in this study). Conceptually, these two aspects could differentially affect perceived control. In the theory of planned behavior, for instance, Ajzen describes two distinct facets of perceived behavioral control, self-efficacy and perceived controllability, that predict behavioral intentions (Ajzen, 1991, 2002). Self-efficacy refers to beliefs of individual performance ability and confidence (Bandura and Wessels, 1997), while perceived controllability refers to the beliefs of individual responsibility and opportunity. Thus, privacy practices, for instance, in disclosure policies, might affect perceived controllability, because they provide the setting for app use and data exchange. Control beliefs, however, are presumably linked to self-efficacy, because they refer to individual actions. In previous research, these constructs differentially affected health behaviors, such as help-seeking (Tomczyk et al., 2020). Hence, their association with privacy concerns warrants further attention.

Moreover, the observed overlap between items measuring anxiety and personal attitudes and the poor fit of the factor requirements receives further support from a study by Buck et al. (2018). In a series of experiments, they aimed to prime privacy concerns and thus incite changes in current perceptions of privacy concerns. In their study, the AIPC showed sufficient sensitivity to change, however, most manipulations affected anxiety and personal attitudes in a similar manner, and there were no significant effects on requirements. These experimental findings mirror the observations of this study, which suggest communalities of anxiety and attitudes, but not requirements. Applying a stronger contextualized focus to app information privacy concerns is therefore beneficial for future research.

Finally, the factors describing anxiety and personal attitudes showed good convergent and discriminant validity, which supports these dimensions of privacy concerns and corroborates previous findings (e.g., Smith et al., 2011; Xu et al., 2012; Dinev et al., 2015; Buck and Burster, 2017). Higher privacy concerns correlated positively with privacy victimhood, and negatively with attitudes and use intentions. And yet, the aspect of requirements (or disclosure and control) did not correlate with any of the variables. However, since privacy concerns were rather high, particularly requirements ($M = 6.12$, SD = 0.70, and range = 1–7), this limits possible statistical associations. Furthermore, explicitly stated privacy concerns as a barrier to tracing app use were not associated with AIPC scores, which challenges their validity. This conclusion is preliminary, because the proportion of participants who stated privacy concerns as a main barrier was rather small (=30/349).

Strengths and limitations

The study investigated a cross-sectional German community sample, therefore it is not representative of the general population. It was also not possible to calculate test-retest reliability or sensitivity to change in this study. Cross-validation in new samples is recommended to inspect generalizability of the identified factor structure. Future studies could also extend psychometric examinations of the scale. The context of COVID-19 contact tracing apps provides an important yet specific scenario to study app information privacy concerns: As pointed out above, health concerns might play an important role in determining privacy concerns, which might not be the case in other use cases (e.g., online banking, e-commerce). This aspect is both a strength and a weakness of the study, because it provides a connection to mHealth research (e.g., Iwaya et al., 2020; Gupta et al., 2021; Hensher et al., 2021), yet it also leads to questions about the validity of these findings for different domains, and potential, health-related confounders

(Hew et al., 2015). The study reported findings for different configurations of AIPC (three- and four-factor models). Nonetheless, future research could examine latent changes and measurement errors more closely in longitudinal models.

Conclusion

The study aimed to test psychometric properties of the AIPC scale (Buck and Burster, 2017). While domains like anxiety and personal attitudes were confirmed in principle, the proposed factor structure was not supported. The analysis instead pointed to a substantial overlap between anxiety and personal attitudes, and a differentiation of requirements into external (disclosure policies) and internal (level of control) expectations of data handling. App information privacy concerns are an important issue in adoption and use of mHealth, as evidenced by negative associations with use intentions and attitudes toward COVID-19 contact tracing apps. And while general concerns and privacy-related attitudes seem to be well understood, motivational processes need further inquiry. Here, the connection between health behavior change, adoption and use of technology and privacy research, is promising.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by University Medicine Greifswald's Ethics Committee. The patients/participants provided their written informed consent to participate in this study.

Author contributions

ST conceived and designed the study, was responsible for data collection, and statistical analysis.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.899092/full#supplementary-material

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BRIEF RESEARCH REPORT
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Usability Study of the iACTwithPain Platform: An Online Acceptance and Commitment Therapy and Compassion-Based Intervention for Chronic Pain

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Background: This pilot study aims to test the usability of the iACTwithPain platform, an online ACT-based intervention for people with chronic pain, to obtain information on which intervention and usability aspects need improvement and on expected retention rates.

Methods: Seventy-three Portuguese women with chronic pain were invited to complete the first three sessions of the iACTwithPain intervention assess their quality, usefulness and the platform's usability. Twenty-one accepted the invitation. Additionally, eight healthcare professionals working with chronic medical conditions assessed the platform and the intervention from a practitioner's point of view.

Results: This study presented a considerable attrition rate (71.43%) among chronic pain participants, with six completers. There were no significant differences in demographic or clinical variables between dropouts and completers except for completed education (participants who dropped out presented less education than completers). Reasons for dropout were related to difficult personal events occurring during the time of the intervention, lack of time, or having forgotten. There seemed to be an overall satisfaction with both the intervention, its contents and form of presentation of information, and the platform, concerning its design, appearance, and usability. Real image videos were preferred over animations or audio by chronic pain participants. Healthcare professionals emphasized the appealing and dynamic aspects of the animation format.

Conclusion: This study informs the ongoing improvement of the iACTwithPain platform and provides valuable information on aspects researchers should consider while developing online psychological interventions for chronic pain. Further implications are discussed.

Keywords: acceptance and commitment therapy, chronic pain, online intervention, usability study, IT

Abbreviations: ACT, Acceptance and Commitment Therapy; SUS, System Usability Scale; M, mean; SD, standard deviation.

INTRODUCTION

Chronic pain can be defined as persistent pain lasting more than 3 months, has a prevalence of approximately 20% in adults (Elliott et al., 1999), can have a detrimental impact in mobility and quality of life (Smith et al., 2001), and productivity (Dorner et al., 2016). Chronic pain is associated with high economic burden, and is considered as one of the most expensive long-term health conditions in industrialized countries (Bernfort et al., 2015; Groenewald and Palermo, 2015; Mayer et al., 2019).

Acceptance of pain is considered an important factor for a successful adaptation to chronic pain, linked to less depression, pain-related anxiety, and disability (McCracken and Eccleston, 2003). These findings have supported the application of acceptance-based therapies, such as Acceptance and Commitment Therapy [ACT; Hayes et al. (2012)], to this population. ACT is an empirically validated psychological approach for chronic pain (APA Presidential Task Force on Evidence-Based Practice, 2006) that promotes acceptance and engagement with values-guided behavior despite chronic pain symptoms (Vowles and McCracken, 2008). The efficacy of ACT for chronic pain has been demonstrated in a meta-analysis by Veehof et al. (2011), and in a broader review including both acceptance and mindfulness-based interventions (Veehof et al., 2016). At the same time, the pertinence of promoting self-compassion [i.e., the ability to be sensitive to personal suffering and being motivated to kindly alleviate it; (Neff, 2003; Gilbert, 2009)] in chronic pain has been highlighted due to its protective role against depressive symptomatology (Carvalho et al., 2018) and the positive effects compassion-focused interventions have presented in this population (Gooding et al., 2020). The combination of ACT and compassion for chronic pain was recently implemented in a pilot test with promising results (Carvalho et al., 2021a).

In recent years, online-delivered interventions have generated increased interest due to their accessibility, flexibility and cost-effectiveness (Bergmo, 2015). In particular, online-based ACT has been proved to be efficacious for chronic pain in a recent meta-analysis. Online-ACT was greater than control conditions in reducing pain interference, pain intensity, depression, and anxiety, and in increasing mindfulness, and psychological flexibility (Trindade et al., 2021a). For these reasons, and additionally considering the advantages of online interventions to improve health-related outcomes (Bergmo, 2015), and for chronic pain in particular (Trindade et al., 2021a), the iACTwithPain intervention platform was developed by the authors of this paper (iACTwithPain research team). iACTwithPain is an ACT- and Compassion-based intervention tailored explicitly to chronic pain. It comprises eight sessions to be completed on an online platform throughout 8 weeks (1 session per week). The efficacy of the iACTwithPain intervention in improving chronic pain impact and related health and quality of life markers will be tested in full in a randomized controlled trial (Carvalho et al., 2021b). It is the aim of the current study to pilot test the usability of the platform by examining the feedback of clinicians and chronic pain patients of first three sessions in order to obtain information on which intervention and usability aspects need improvement, and on expected retention rates. Given our team's combined expertise in psychology, design and engineering, we hypothesize qualitative feedback from participants reflecting pertinent content for patients with chronic pain, and an online platform that is intuitive, engaging and esthetically pleasing. We additionally expect high usability scores, as measured by the System Usability Scale [SUS; Martins et al. (2015)], relating to participants' use of the platform.

METHODS

Ethical Approval and Data Safety

This study was approved by Ethical Committee of the Faculty of Psychology and Educational Sciences of the University of Coimbra (on 28/11/2019), and was conducted in accordance with the ethical standards in the 1964 Declaration of Helsinki and its later amendments. All collected data will be stored (for 5 years) using high standard security mechanisms, and thus ensuring confidentiality. Data will be in anonymized and can only be assessed by the research team.

Sample Size Calculation

According to Faulkner (2003), on average, a sample of five participants can detect 85% of the usability problems. Therefore, we aim to have a sample of at least 5 in each group (participants with chronic pain and health professionals). Assuming a conservative dropout rate of 83% (Bangor et al., 2009) for the clinical sample, at least 30 participants should be invited to enroll in the study.

Procedures

The study's chronological order was as follows: (1) participants recruitment (presentation of the study and informed consent); (2) during the following 2 weeks participants tested the iACTwithPain platform; (3) in the third week the usability and quality assessment questionnaire was administered; (4) participants who dropped out from the study were contacted to fill in a questionnaire (reasons for dropping out).

Seventy-three Portuguese women with chronic pain, enrolled in a different study who had demonstrated interest in taking part in the current one, were invited to complete the first three sessions of the iACTwithPain intervention and assess their quality and usefulness, as well as to assess the platform's usability. Inclusion criteria were: age between 18 and 65 years; diagnosis of chronic pain; internet access; and proficiency in Portuguese. Exclusion criteria were: not providing informed consent; or pain due to malignancy, trauma, or surgery. Twenty-one accepted the invitation to participate, signed an informed consent, and were enrolled in the study. Participants with chronic pain that did not complete the three sessions were asked to fill out a questionnaire on the reasons for attrition.

Additionally, nine healthcare professionals working with chronic medical conditions (four psychologists, four physicians, and one nurse) were also invited to assess the platform and the intervention from a practitioner's point of view. Of these, eight signed an informed consent before the start of the study and were enrolled in the study.

The iACTwithPain Platform

The iACTwithPain intervention was designed based on the psychological flexibility model (Vowles and McCracken, 2008; Trindade et al., 2020) and compassion-focused interventions applied to chronic pain (Carvalho et al., 2018). The psychologists' members of the iACTwithPain team have expertise in developing and efficacy testing ACT and compassion-based interventions for chronic conditions such as chronic pain (Carvalho et al., 2021b), cancer (Trindade et al., 2020), inflammatory bowel disease (Trindade et al., 2021b), and psychiatric disorders (Duarte et al., 2017). Moreover, the team's knowledge of the psychological impact of chronic pain and the underlying psychological processes (Carvalho et al., 2018, 2019, 2021c) were taken into consideration. During iACTwithPain development, the principles of ACT and compassion-based interventions were strictly followed to ensure pertinent and rigorous therapeutic sessions. As described in the RCT protocol (Carvalho et al., 2021b) treatment integrity guidelines for ACT (Plumb and Vilardaga, 2010) were followed and included: (a) training in ACT and compassion focused therapy models, ensuring that the therapists fully grasp the concepts and principles of the interventions and have previous competence/experience in their application; (b) the content of the sessions are ACT-consistent (for example focus on the function rather than the content); and the known processes of change of ACT and compassion were followed during the development of the intervention.

Participants will be randomly assigned to two experimental arms: and ACT-only intervention or an ACT and compassion-focused intervention. All sessions will be the same except for sessions five and six. The ACT and compassion-focused group will be exposed to compassion themes and exercises (e.g., what is compassion, developing compassion toward the self and others, obstacles to compassion). The ACT-only group will reinforce previous topics (e.g., willingness, acceptance, defusion, and observing self) without introducing new information or practices. The ACT intervention will include the following core themes: (a) Awareness of internal experiences (mindfulness; self-as-context); (b) Openness to experience difficult experiences (acceptance of pain: willingness toward thoughts, emotions and physical sensations; and cognitive defusion); (c) Engagement with valued action (values clarification and commitment to meaningful actions); (d) Self-Compassion (promoting self-kindness in times of difficulty; for the ACT and compassion-focused group only). Sessions will comprise video-animations (with videoscribes and therapists' avatars), real-image videos, texts, and audios guiding meditative practices. iACTwithPain is a self-paced intervention and therefore the participant can decide when to login and complete each session. Nevertheless, the intervention was designed so that sessions are completed weekly (one session per week, over 8 weeks). Each new session will become available in the platform every Monday. Emails notifying the participants that a new session is available will be sent weekly.

Session 1 is completed immediately after session 0, and the following sessions are then completed once per week. A brief introductory session (session 0) will welcome participants to the intervention and introduce the platform. Participants are asked to practice between-session mindfulness and/or compassion-based meditative exercises as often as possible. In this usability study, participants were asked to complete the introductory session (session zero), session one and two. Session one focuses on psychoeducation about chronic pain, promotion of creative hopelessness, introduction to mindfulness practice, and mindfulness of breathing practice. Session two focuses on the usefulness of mindfulness to manage suffering, promotion of mindfulness practice, and body scan practice (see **Table 1** for more detailed information). Mindfulness exercises throughout the intervention focus on a non-judgmental, open, and accepting attitude toward the present moment. Visual examples from these sessions are presented in **Figure 1**.

Measures

Primary Outcome

Both groups of participants (patients and professionals) were asked to complete the SUS [(Brooke, 1996); original validation (Bangor et al., 2008); portuguese validation (Martins et al., 2015)]. This scale is robust and widely used to evaluate the usability of products and user interfaces (Bangor et al., 2009). The European Portuguese validation is equivalent to the original version in terms of semantics and content, and presented good psychometric properties e.g., high convergent validity and satisfactory inter-rater percentage of agreement (Martins et al., 2015). It provides a single reference score for participants' view of the usability of a product or service. It comprises ten items rated on a 5-point Likert scale (1: Strongly Disagree; 5: Strongly Agree) and has been shown to present adequate psychometric properties (Bangor et al., 2008). The SUS items were coded by subtracting 1 from the odd items' score, subtracting even items' score from 5 (correction for the reverse scored items), and multiplying the re-coded values by 2,5 (Martins et al., 2015). This results in new scores ranging from 0 to 100, where higher scores indicate better usability. According to the adjective ratings proposed by Bangor et al. (2008), SUS scores from 0 to 25 are "Worst imaginable," 25–39 "Poor," 39–52 "Ok," 52–73 "Good," 73–85 "Excellent," and 85–100 are "Best imaginable" (Bangor et al., 2008).

Secondary Outcomes

Participants with chronic pain and healthcare professionals were asked to complete a set of self-report questions regarding the quality of the intervention (e.g., content clarity, pertinence of the intervention themes, platform design and organization, individual session quality), session duration, and preferences

TABLE 1 | Structure and contents of session 0, 1, and 2.

Topic	Content/Exercise	Format
Session 0 – Introduction to the intervention and the platform		
Welcome video	Information about the nature and structure of the program, and its objectives.	Real-image video with a therapist
Navigation of the platform	Presentation of the platform and information regarding its navigation (including instructions and steps to move through the program)	Real-image video
Motivation and intentions clarification	Contemplative exercise "Exploring my motivations to do this intervention"	Real-image video with a therapist
Session 1 – Psychoeducation and creative hopelessness		
Check-in	Brief exercise to focus and anchor on the present moment (a soft landing exercise).	Video-animation with a therapist avatar
Psycho-education about chronic pain	Multidimensional phenomenon of pain: video about the function of pain, how it manifests itself in the body, and its various components.	Real-image video with a therapist
The problem with our problem-solving minds (controlling is the problem)	Video about how the human mind works and how it attempts to control unpleasant internal experiences, and consequently generating suffering and exacerbating our problems.	Videoscribe animated video
Promotion of creative hopelessness	Video about exploring alternative ways of relating to our sensations, thoughts, memories and emotions. One of the core competencies that will be developed in the iACTwithPain program is the ability to be in the present moment. This competence will be developed through mindfulness training.	Real-image video with a therapist
Introduction to mindfulness practice	Instructions on proper posture to perform contemplative practices (appropriate body postures for the contemplative practices are exemplified).	Real-image video with a therapist
	Mindfulness of breathing practice.	Audio
Between-session assignment	Mindfulness of breathing practice.	Audio
Session 2 – The body as an anchor on the present moment		
Check-in	Brief exercise to focus and anchor on the present moment (a soft landing exercise).	Video-animation with a therapist avatar
Mindfulness as a key aspect to manage suffering	Video presenting what Mindfulness is and its benefits.	Real-image video with a therapist
Therapists' personal experience with mindfulness: Tips for maintaining regular practice	In this video, therapists share their personal experience with mindfulness. Not only the difficulties experienced, but also the benefits obtained, resulting from a frequent and committed practice.	Real-image video with a therapist
The body as an anchor to the present moment	In our body everything is integrated. All systems, organs, muscles and nerve endings are interconnected and communicate with each other. Our emotions also manifest in the body (for example when we are anxious, we may feel tension in the muscles or the heart beating faster). Video about the complex entity that is the body, and exploration of usual and alternative ways of relating to our emotions, thoughts, and feelings, as inhabitants of the body.	Videoscribe animated video
Between-session assignment	Mindful movement (Qigong)	Real-image video with a therapist
	Body scan meditation	Audio

Information partly retrieved from Carvalho et al. (2021b).

on type of presentation format (e.g., video, audio). These questions were developed by the research team to tailor to the specific platform characteristics that this study aims to assess. The platform kept track of participant engagement concerning the number of logins in the platform and engagement with mindfulness practice audios or videos.

Statistical Analyses

All analysis were performed on SPSS (Statistical Package for the Social Sciences), version 25 (IBM Corp., Armonk, NY, United States). Descriptive and frequency analyses were conducted to analyze participants' evaluations of the platform/intervention, as well as engagement with the platform. Mann–Whitney U and Fisher's exact test were conducted to analyze differences between groups of participants (e.g., completers, dropouts). The retention rate was computed as the proportion of participants that completed the three sessions.

RESULTS

In this study we aimed to pilot test the usability of the iACTwithPain platform, in what concerns our primary outcome – usability scores; and secondary outcomes – qualitative assessment, engagement, and retention rate.

Primary Outcome – Usability

Sample of Participants With Chronic Pain

Regarding usability scores (SUS), on average, iACTwithPain's platform was rated as excellent ($N = 5$, $M = 76.50$, SD = 16.83).

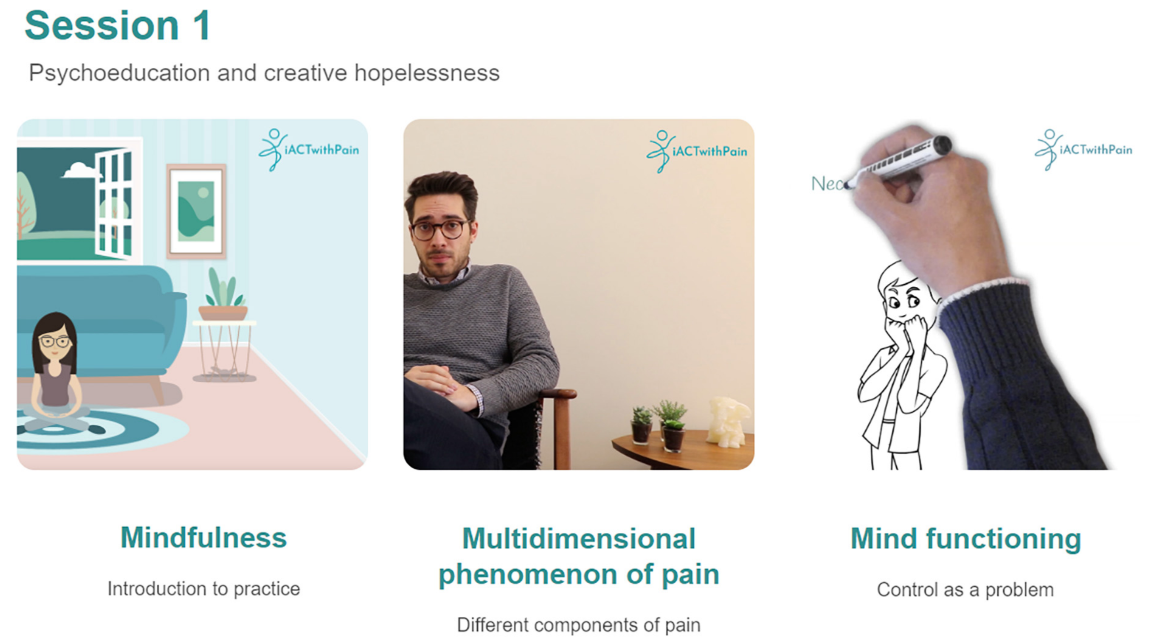

FIGURE 1 | Example of session 1 contents depicting the three types of videos (left to right: video-animation with a therapist avatar, real-image video with a therapist, and videoscribe animated video).

Two participants rated it as good ($M = 58.75$, SD = 1.77), one rated it as excellent (82.5), and two rated it as best imaginable ($M = 91.25$, SD = 5.30).

Sample of Healthcare Professionals

On average, the iACTwithPain's platform usability (SUS) was rated by healthcare professionals as excellent ($N = 5$, $M = 84.50$, SD = 7.79). Two participants rated it as excellent ($M = 80.00$; SD = 2.50), and three as best imaginable ($M = 91.25$; SD = 8.84).

Secondary Outcomes – Qualitative Assessment, Engagement, and Retention Rate

Qualitative Assessment of the iACTwithPain Platform

Sample of Participants With Chronic Pain

Of the six completers, three preferred real image video format, two preferred animations, and one preferred sole audios. **Table 2** presents participants' feedback on each of these formats. Written feedback highlighted advantages to the real image video format, which was overall described as attractive and motivating to practice. One comment indicated that more investment in the background of the real-time videos should be made and that these videos could include animations. Described advantages for the audio format were accessibility and having less distractions. Animation videos were described as interesting and having an attractive and simple design.

Concerning other aspects of the intervention and platform, participants generally rated positively their satisfaction (on a scale from 0, no satisfaction, and 10, extremely satisfied) with the platform's design ($M = 7.50$; SD = 2.01), color pattern ($M = 8.33$; SD = 1.37), and attractiveness ($M = 7.67$; SD = 1.75).

The topics covered by the two assessed sessions were very positively evaluated ($M = 8.67$; SD = 1.03). The topics found most useful to participants ($n = 4$) were psychoeducation about pain ($n = 1$), mindfulness of breathing ($n = 1$), and body scan practice ($n = 2$). Participants also provided positive answers (on a scale from 0, no satisfaction, and 10, extremely satisfied) regarding their interest in continuing the intervention ($M = 7.33$; SD = 3.20). Furthermore, four participants provided feedback on what they believe could be changed to improve these three sessions. One participant indicated that the sessions seemed to cover all important aspects. Another referred to longer intervals without instructions in the mindfulness practices, and two stated that they felt that strategies to reduce pain should be included in the intervention.

Sample of Healthcare Professionals

The healthcare professionals group seemed to prefer the animation ($n = 3$) and real image video ($n = 2$) formats. Real image videos ($M = 34.20$; SD = 2.68) and animations ($M = 33.60$; SD = 1.67) were overall more positively evaluated than audios ($M = 27.80$; SD = 3.49). Overall, written feedback about the audios indicated that this format is easy to use and accessible, although not particularly appealing or stimulating. Animations were described as attractive, and appealing, but impersonal. Real image videos were described as providing a connection with the therapeutic team and the opportunity to get to know the therapists better. Some technical issues were also identified regarding this format (e.g., indications

TABLE 2 | Participants' feedback on the different kinds of content format (*n* = 6).

Questions	Participants endorsing each response category, *n*					*M* (SD)
	1. Strongly disagree	2. Slightly disagree	3. Neither disagree nor agree	4. Slightly agree	5. Strongly agree	
Audio						34.16
Easy to use	0	0	0	2	4	4.67 (0.52)
I got easily distracted	1	1	0	3	1	3.33 (1.52)
Interesting	0	0	0	4	2	4.33 (0.52)
I would use this format again	0	0	0	4	2	4.33 (0.52)
Appropriate lenght	0	1	0	3	2	4.00 (1.10)
Has technical quality	0	2	0	2	2	3.67 (1.37)
Boring and uninteresting	4	1	0	1	0	1.67 (1.21)
Message is clear and easy to understand (*)	0	0	0	2	3	4.60 (0.55)
Appealing and increases motivation	0	0	0	4	2	4.33 (0.52)
Animation						35.60
Easy to use (*)	0	0	0	3	2	4.40 (0.55)
I got easily distracted (*)	2	2	1	0	0	1.80 (0.84)
Interesting (*)	0	0	0	2	3	4.60 (0.55)
I would use this format again (*)	0	0	0	2	3	4.60 (0.55)
Appropriate lenght (*)	0	0	0	3	2	4.40 (0.55)
Has technical quality (*)	0	0	0	1	4	4.80 (0.45)
Boring and uninteresting (*)	4	0	0	1	0	1.60 (1.34)
Message is clear and easy to understand (*)	0	0	0	1	4	4.80 (0.45)
Appealing and increases motivation (*)	0	0	0	2	3	4.60 (0.55)
Real image video						36.66
Easy to use	0	0	0	1	5	4.83 (0.41)
I got easily distracted	2	1	1	2	0	2.50 (1.38)
Interesting	0	0	0	2	4	4.67 (0.52)
I would use this format again	0	0	0	2	4	4.67 (0.52)
Appropriate lenght	0	0	0	2	4	4.67 (0.52)
Has technical quality	0	0	1	1	4	4.50 (0.84)
Boring and uninteresting	4	1	0	1	0	1.67 (1.21)
Message is clear and easy to understand	0	0	0	2	4	4.67 (0.52)
Appealing and increases motivation	0	0	1	1	4	4.50 (0.84)

(*) one participant did not respond to these topics.

to improve the flow of the video cuts; audio and video synchronization).

Healthcare professionals presented favorable ratings on other aspects of the platform (on a scale from 0, no satisfaction, and 10, extremely satisfied): design (*M* = 8.40; SD = 1.52), color pattern (*M* = 8.80; SD = 1.30), and attractiveness (*M* = 8.40; SD = 1.34).

Concerning the contents of the intervention, positive ratings were also provided (0, no satisfaction – 10, extremely satisfied) for all assessed items: content quality (*M* = 9.60; SD = 0.55), pertinence of the topics (*M* = 9.40; SD = 0.89), topics sequencing (*M* = 8.60; SD = 0.55), and appropriateness of therapists' posture (*M* = 9.20; SD = 0.84).

Participant Engagement and Retention

The completers' sample logged into the platform on average 16.33 times (SD = 12.91), and evaluated the first session on average as 4 (SD = 0.63), and the second session as 3.83 (SD = 0.75), both on a scale of 1–5. In what concerns home practice, completers practiced on average 2.67 times (SD = 3.20) the practice from session one (mindfulness of breathing), and 2.20 times (SD = 2.68) the practice from session 2 (body scan).

The dropout sample logged into the platform on average 3.33 times (SD = 3.90). Four of these participants completed the first session, assessed it as 4.5 on average (from 1 to 5; SD = 0.58), and did the practice from session one on average 1.75 times (SD = 0.96). No participant from the dropout group assessed the second session nor engaged in the second practice.

Reasons for Dropout

Six of the 12 participants that dropped out from the study completed the attrition questionnaire. Three participants indicated a difficult personal situation after the beginning of the study as the reason for dropout, two referred to lack of time, and one referred to having forgotten to complete the intervention (although participants were reminded once a week to complete the sessions). No participant referred to any reason associated with the platform or the intervention. Two participants provided additional feedback, indicating that: (1) “it looked very well structured, simple, and potentially very useful”; and (2) “I really liked the intervention’s contents and how the platform was structured. I had a problem with the login once, but it was quickly fixed.”

Descriptive Statistics

Sample of Participants With Chronic Pain

The demographic and clinical characteristics of the participants that accepted to participate, the ones who dropped out, and the completers are presented in **Table 3**.

There were no statistically significant differences between completers and participants who dropped out regarding age, time since chronic pain diagnosis, chronic pain diagnosis, and diagnosis of comorbid medical conditions. However, there were significant differences regarding education - participants that dropped out presented less education. The final sample of completers was composed of women with chronic pain with ages between 35 and 65 years.

Sample of Healthcare Professionals

Regarding the group of healthcare professionals, out of the eight professionals that signed an informed consent, five (four psychologists and a physician) provided feedback. These five professionals, four women and a man, had worked in chronic pain contexts between 5 and 20 years (M = 10.40; SD = 6.19) in hospitals in the North and Center regions of Portugal.

DISCUSSION

Overall, the pilot usability study of the iACTwithPain platform (and first three sessions: 0, 1, and 2) presented promising results in terms of usability scores (high for both clinical and healthcare professionals samples), quality assessment of the different content delivery methods, and engagement metrics. Qualitative feedback from participants and health professionals will be taken into consideration for the development of the full iACT intervention, and measures to avoid dropout will be adopted.

Of the six chronic pain participants that completed this pilot test, and the five healthcare professionals that provided feedback, there seemed to be an overall satisfaction with both the intervention, regarding its contents and form of presentation of information, and the platform, concerning its design, appearance, and usability. Real image videos, mainly used to introduce new topics, provide rationales, or exemplify the possible meditation positions, appeared to be more preferred than animations or audios by chronic pain participants. This was possibly due to a perception of “being closer” to the therapists, provided by the real image videos, which may help participants feel understood and find the motivation to practice. It may also be hypothesized that real image videos are more effective in tapping into tacit cognitive-emotional factors of efficacy in psychotherapy, such as an empathic and compassionate therapeutic relationship, which is more difficult to convey through non-human avatars. This was highlighted by healthcare professionals’ feedback, who nonetheless also emphasized the appealing and dynamic aspects of the animation format. However, for meditative practices, the audio format should have preferred use over real image videos or animations to avoid unnecessary distractions during practice. Finally, two participants with chronic pain indicated that they believed that strategies to reduce pain should be included in the intervention. Even though the first session of the iACTwithPain intervention states the rationale for accepting pain rather than attempting to reduce or control it (Vowles and McCracken, 2008), and the negative effects of doing the latter (McCracken et al., 2007), it seems that these participants still held on to the idea that pain must be avoided to lead a satisfactory life. Still, participants had only completed the two first sessions of the intervention, where ACT’s acceptance and values topics are not clearly focused on (these topics are presented more in-depth in later sessions). Therefore, it might be beneficial for the future RCTs to increase the focus on acceptance earlier in the intervention, by including, for example, experiential acceptance exercises or metaphors.

The study attrition rate was of 71.43%. Out of the 21 participants that signed the informed consent, 12 (57.14%) accessed the intervention, and 6 (28.57%) completed the study. No significant differences in demographic or clinical variables were found between dropouts and completers except for completed education, with participants who dropped out presenting less education than completers. This result is in line with findings from previous research, where lower educational level was associated with higher risk if dropping out (Karyotaki et al., 2015). Motives for dropout, offered by 6 of the 12 participants who did not finish the intervention, were unrelated to the intervention or platform. There were reasons related to difficult personal events occurring during the intervention, lack of time, or having forgotten. Similar results were found in a review about reasons for dropping out in ACT interventions (Karekla et al., 2019). The iACTwithPain platform will thus include mechanisms to identify when participants have not logged in to the platform for 3 days in a row, so the team can send engagement reminders to these participants. This strategy is aligned with previous studies showing that contingent reminders can improve motivation and boost behavior change (Webb et al., 2010). If emails are not enough to engage non-responsive participants, phone calls will be implemented, since previous online-based studies have suggested that closer contact with the therapist is associated with lower dropout rates (Cuijpers et al., 2008; Macea et al., 2010). Still, given that only half of the participants who dropped out provided reasons for having stopped participating, it is difficult to know whether the platform/intervention did not influence some participants’ dropout. Other factors that we did not account for might be influencing dropout, namely comorbid depression or anxiety, relationship status, or chronic pain severity, according to a review by Melville et al. (2010). The attrition rate presented by this study falls within the range of 2–83%, presented by a review on dropout rates from online treatments for psychological disorders (Melville et al., 2010). It should nonetheless be noted that the current intervention

TABLE 3 | Descriptives and frequencies of the demographic and clinical variables in study across groups, and tests of differences between participants who dropped out and completers.

		Accepted to participate (N = 21)	Dropped-out (N = 12)	Completers (N = 6)	Test of differences		
					Mann Whitney U	**Fisher's exact test**	***p***
Age, *M* (SD)		45.35 (6.70)	45.09 (4.01)	46.67 (11.55)	−32.50	–	0.960
Education, *n* (%)	Middle school	1 (4.80)	1 (8.30)	–		10.32	0.007
	High school	8 (38.10)	4 (41.70)	–			
	BSc degree	6 (28.60)	2 (16.70)	4 (66.70)	–		
	Post-graduation	4 (19.00)	4 (33.3)	–			
	MSc degree	2 (9.50)	–	2 (33.3)			
Time since diagnosis, *n* (%)	1–5 years	5 (23.80)	1 (8.30)	3 (50)	–	3.65	0.177
	5–10 years	4 (19.00)	3 (25.00)	1 (16.70)			
	10+ years	12 (57.10)	8 (66.70)	2 (33.30)			
Chronic pain diagnosis, *n* (%)	Fibromyalgia	16 (76.20)	9 (75.00)	4 (66.70)	–	3.42	0.769
	Rheumatoid arthritis	2 (9.50)	1 (8.30)	1 (16.70)			
	Sjogren Syndrome	1 (4.80)	1 (8.30)	0 (0)			
	Low back pain	1 (4.80)	0 (0)	1 (16.70)			
	Scleroderma	1 (4.80)	1 (8.30)	0 (0)			
Comorbid medical condition diagnosis, *n* (%)	Yes	11 (52.40)	5 (41.70)	4 (66.70)		–	0.620
	No	10 (47.60)	7 (58.30)	2 (33.30)			

M, mean; SD, standard deviation.

is directed at people with chronic pain, and most importantly, that this is a usability study, in which participants may present less motivation to participate in comparison with a trial of a full intervention.

This usability study will improve the iACTwithPain platform by informing which type of format is preferred and which one works best for each type of content. Considering feedback from the participants, the real image videos with therapists were overall preferred and viewed as engaging and motivating, so we will mostly select this format in the future intervention. Nevertheless, all types of exercises will be maintained (animations, videoscribes, real image videos, and audios), since some participants showed preference for these formats and since this will allow for a more varied and stimulating user experience. The audio format will be selected for guided exercises (e.g., 80th Birthday Party) or meditations (e.g., body scan), since participants reported that this format helped them maintain focus on the instructions of the exercises. Participants did not provide negative feedback regarding the attractiveness, navigation or esthetic elements (e.g., design and color pattern) of the platform. Therefore, no changes will be made to these elements. Finally, weekly automatic and contingent reminders (when a participant does not login in for three consecutive days) will be implemented to reduce the likelihood of participants dropping out from study.

This study has some limitations that are worth discussing. We did not assess previous experience with acceptance or compassion-based psychological interventions, so it was not possible to control the possible confounding effect of previous knowledge/experience on these approaches. The small sample size might have influenced the results obtained and might not generalize to broader samples. Only women enrolled in this study (although this was not a criterion for this study), which limits generalization of these results to male chronic pain samples. However, this usability study allowed the initial test of the iACTwithPain platform and provided valuable insights for developing the full intervention. A future feasibility study informed by the current one is being conducted by the iACTwithPain team and will assess several recruitment pathways/strategies, as well as the full intervention (both quantitatively and qualitatively).

The present study has informed the improvement of the iACTwithPain platform before its final testing in a larger clinical trial. In addition, this study provides useful information on some aspects researchers should consider while developing online psychological interventions for chronic pain.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the Faculty of Psychology and Educational Sciences, University of Coimbra, Portugal. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

IT: conceptualization, data curation, formal analysis, and writing—original draft, review and editing. RG: data curation, formal analysis, and writing—original draft. SC, PM, MN, TL, JD, and JP-G: writing—review and editing. BP: data curation and writing–review and editing. PC: funding acquisition, conceptualization, supervision, and writing—review and editing. All authors read and approved the final manuscript.

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