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Making Mobile Health Information Advice Persuasive:
An Elaboration Likelihood Model Perspective

Jinjin Song, Harbin Institute of Technology, China
Yan Li, Harbin Institute of Technology, China
Xitong Guo, Harbin Institute of Technology, China
Kathy Ning Shen, United Arab Emirates University, UAE
Xiaofeng Ju, Harbin Institute of Technology, China

ABSTRACT

As m-health apps become more popular, users can access more mobile health information (MHI) through these platforms. Yet one preeminent question among both researchers and practitioners is how to bridge the gap between simply providing MHI and persuading users to buy into the MHI for health self-management. To solve this challenge, this study extends the elaboration likelihood model to explore how to make MHI advice persuasive by identifying the important central and peripheral cues of MHI under individual difference. The proposed research model was validated through a survey. The results confirm that (1) both information matching and platform credibility, as central and peripheral cues, respectively, have significant positive effects on attitudes toward MHI, but only information matching could directly affect health behavior changes; (2) health concern significantly moderates the link between information matching and cognitive attitude and only marginally moderates the link between platform credibility and attitudes. Theoretical and practical implications are also discussed.

KEYWORDS

Elaboration Likelihood Model, Health Behavior Changes, Health Concern, Health Information Matching, Mobile Health Information, Platform Credibility

INTRODUCTION

With the rapid development and popularization of mobile communication technology, a wide variety of M-Health apps has emerged, and the global estimated size of the M-Health app market is forecast to exceed 11 billion dollars by 2025[1]. These M-Health apps not only offer online diagnosis support from a physician but also provide users with mobile, convenient, flexible, and personalized mobile health information (MHI) or knowledge, which is expected to help enhance users' involvement in health management and health behavioral changes (Xie et al., 2018; Chao et al., 2019). However, exposure or access to health information does not guarantee the adoption of health-related suggestions and subsequent behavioral changes (Liobikienė & Bernatonienė, 2018). The question of how to bridge the gap between simply providing MHI and persuading users to accept the MHI and change their health behaviors, therefore, remains a preeminent issue for both researchers and practitioners.

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To further understand this question, our study applies the elaboration likelihood model (ELM) to examine how the MHI might be made to persuade users to change their attitudes and health behaviors. The ELM is often used to explain how different processing conditions influence the persuasion routes (central cues vs. peripheral cues) by which individuals come to change their attitudes and behaviors (Petty & Cacioppo, 1986). The central cues are mainly about the quality or relevance of arguments around an issue or a target, and the peripheral cues are derived from the identification with the sources (Bhattacherjee & Sanford, 2006). Given the strength of dual modes of persuasion, ELM has been widely used in the adoption and usage of M-Health technology or services (Guo et al., 2020; Cao et al., 2020), however, how different mechanisms can be used to make MHI more persuasive has received minimal attention.

Previous studies in the M-Health context tend to focus on the central route of persuasion, as health-related decisions are usually considered high involvement (Zhang et al., 2018; Meng et al., 2019). Most prior studies focus on service quality, information quality, or argument quality as central-route persuasion cues (Chen et al., 2018; Handayani et al., 2020). However, for recipients with diverse health conditions, effective dissemination of health information requires adequate personalization of information (Swan, 2012). Recent research also implies that matching M-Health services and personalizing health knowledge are crucial factors in persuasion (Wang et al., 2018; Zhang, 2013), especially through the central persuasion route in ELM (Tam & Ho, 2005). Nonetheless, how information matching as a central persuasion cue persuades users to change attitudes and health behaviors in the M-Health context is seen to have been understudied.

In addition to the content characteristics of MHI, the source characteristics of MHI also matter to users (Huo et al., 2018). Previous studies have demonstrated that a source's credibility encourages use intention among M-Health service users (Meng et al., 2019; Chen et al., 2018). Another critical consideration for M-Health apps is the use of information source authentication mechanisms, which help assure users that the health information is being supplied by individuals or groups with the necessary domain expertise (Huo et al., 2018). For instance, some apps identify a professional physician as the source (such as haodf.com in China or the WebMD in the U.S.), while others only provide a content endorsement by the platform. It is not known whether the use of platform credibility as source credibility can change patients' attitudes towards MHI and then change their health behaviors, and this question is worth further exploration. Therefore, we still use platform reliability as the peripheral cue. Consequently, we propose our first research question: "*What are the persuasion effects of information matching and M-Health platform credibility on users' attitudes and behavior changes?*"

Furthermore, health concern reflects an individual's worry of fears about the unexpected potential disease risk. Scholars have shown that health concern as a personal characteristic is an important variable in patients' health-related decisions (Marakhimov & Joo, 2017). Prior studies also found that individuals with perceived health threat or strong health concern require particularly compelling arguments to modify their belief structure (Huo et al., 2018). However, Recent studies about ELM in M-Health pay more attention to the moderating effect of positive health assessment (e.g., e-Health literacy, health consciousness) on the persuasion process (Meng et al., 2019; Zhang et al., 2018). It is still unclear how health concern as an individual's negative attention to his/her health moderates persuasion paths. Thus, we propose our second question: "*What is the moderating effect of health concern on the influence of MHI cues on individual attitude changes and health-related behaviors?*" Answers to this question will help researchers and practitioners to understand which persuasion route is more effective for users who may be panicking or afraid of disease risk.

The rest of this paper is organized as follows: In the next section, we review the literature on online health information and the Elaboration Likelihood Model in M-Health context. Then, we propose our research model and hypotheses based on the ELM. In the following sections, we present the methodology and the results, respectively. Finally, we discuss the results, implications, and limitations of this study.

LITERATURE REVIEW

Health Information in the M-Health Context

M-Health apps mainly focus on health management, which could increase access to health medical information and knowledge without temporal and geographical constraints. Mobile health information as a medical knowledge service module in M-Health apps (e.g., health-related articles and Q&A pages) plays important roles in improving users' health knowledge literacy and understanding of their therapeutic choices, which could help users make better health behavior decisions (Huo et al., 2018; Ghaddar et al., 2011) .

Although these M-Health providers sometimes overlap in their services, these M-Health apps still have inherent design differences. First, they have differentiated information recommendation algorithms to meet patients' heterogeneous needs. For instance, some apps make recommendations based on the user's disease type, while some may make recommendations according to users' online browsing preferences and behaviors. Second, given that the provider of health information is one of the keys to users' acceptance of health advice (Major & Coleman, 2012), different M-Health apps also have their unique authentication mechanisms for health information sources. It has been shown that authoritative and reliable health information sources generally include official hospitals, physicians, and official healthcare organizations, while other sources usually refer to unofficial (Huo et al., 2018; Major & Coleman, 2012). In the M-Health context, some platforms mainly recommend MHI identified by physicians (such as haodf.com in China and WebMD in the U.S.), some recommend MHI identified by the platform (such as Chunyuyisheng.com in China), and some recommend health information headlines that are integrated from multiple sources (including both official organizations and those unofficial health-related public accounts) and redistributed by the platforms. However, most previous studies of M-Health apps have assumed that these platforms are similar and did not subdivide them. Given this lack of distinction, studies to date have not identified what health information transmission mechanisms are the most important for M-Health apps, a gap that this study aims to address.

MHI: From Usage to Persuasion

The ultimate purpose of M-Health apps is not just to get users to adopt and use the technology; rather, the main goal is to promote users' health self-management and health behavior changes. Research on the Technology Acceptance Model and Continuance Theory Model is not enough to explain how MHI persuades individuals to change health behaviors. One explanatory possibility is the ELM, which is a dual-process theory that describes the how different message cues persuade individuals to change their attitude and behaviors (Petty and Cacioppo, 1986; Fazio and Zanna, 1981). Thus, the ELM is well suited to help us reach a better understanding of our central question: how to make MHI persuasive. And then, we briefly review the existing studies on the ELM, both in general and specifically in M-Health.

The Elaboration Likelihood Model in M-Health

The ELM emphasizes the dual process of persuasion (i.e., the central and peripheral processes) for modeling the factors that impact an individual's attitude formation (Petty & Cacioppo, 1986; Fazio & Zanna, 1981). In the central persuasive process, information recipients expend more cognitive effort in analyzing the quality of the arguments. In the peripheral persuasive routes, individuals' attitude formation is derived from simple identification cues, such as the credibility of message sources(Petty et al., 1981).

The two persuasion routes can further be restricted and modified by the "elaboration likelihood", that is, the user's depth of involvement. When individual involvement is high, the persuasion process is more likely to rely on the central cues. In contrast, when individual involvement is low, the persuasion process would be more attached to the peripheral cues (Petty et al., 1981). The elaboration likelihood is also constructed as individuals' abilities or motivations (Petty & Cacioppo, 1986). A higher motivation or ability would motivate an individual to give greater consideration to processing the information related to the key arguments, and thus the persuasion process of individual cognition is more likely to take place through the central route than the peripheral route.

Given the ELM's strength in explaining the dual process of persuasion, it has also been used in M-Health research as the theoretical lens. Table 1 provides a brief overview of the most relevant and representative empirical studies in this research field.

Table 1. Overview of prior studies on M-Health services

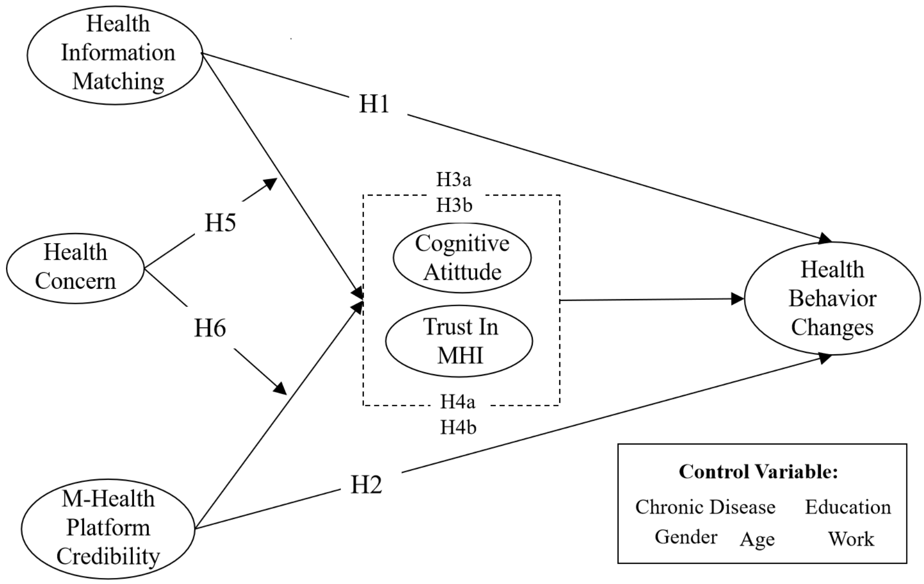
Ref.	Dependent Variable	Central Cues	Peripheral Cues	Elaboration Likelihood
Zhang et al. (2018)	Trust in Vendor, Continuance Usage Intention of M-Health apps	Scrutinizing Information	System Quality	e-Health Literacy
Meng et al. (2019)	Routine Use Intention of M-Health Services	M-Health Argument Quality	Source Credibility	Health Consciousness
(Gu et al., 2017)	Privacy Concerns, M-Health App Download Intention	Perceived Permission Sensitivity/ Justification	Perceived App Popularity	Mobile Privacy Victim Experience
Chen et al. (2018)	Continuance Intention Regarding M-Health Apps	Doctors' Service and Information Quality	Apps' Reputation & Apps' Institute Assurance	Privacy Concern
Handayani et al. (2020)	Satisfaction with M-Health, Routine Use Intention, Loyalty to M-Health	Information Quality	M-Health Source Credibility	None
(Guo et al., 2020)	Continuous Usage Intentions Regarding M-Health Services	Information Quality	System Quality, Social Media Influence	Health Consciousness
(Cao et al., 2020)	Trust in Doctor/Platform, Adoption Intention	Doctors' Performance Cues	Platforms' Performance	None

Research on ELM in the M-Health context has mainly focused on the adoption and usage of M-Health apps or services, losing sight of how MHI, as an important medical knowledge module, persuades users to change attitudes and health behaviors. Furthermore, previous studies mostly consider the central persuasive effect of service and information quality, ignoring the personalized characteristics of MHI services and users' heterogeneous demands. Finally, most existing studies consider the moderating effect of users' positive health cognition (e.g., e-health literacy), but seldom from the perspective of individuals' negative attention to health. Therefore, we focus on the MHI in M-Health and explore how to make it more persuasive to change individuals' attitudes and health behaviors based on the ELM.

HYPOTHESIS DEVELOPMENT

Based on ELM and M-Health literature, we construct a behavior change model by identifying the central (i.e., information matching) and peripheral (i.e., platform credibility) persuasion processes related to MHI, and further identifying the moderator (health concern) of above relationships based on individual characteristics. The research model is shown in Figure1.

Figure 1. Research Model



Effects of Information Matching and Platform Credibility on Health Behavior Changes

Health information matching describes the fitness between health information contained in M-Health platforms and individuals' health needs (Tam & Ho, 2005), and it is much more significant in influencing individuals' decisions. Specifically, personalized health information with a high matching level might decrease users' cost of searching for information, thus improving an individual's efficiency in obtaining useful health information and enabling users to obtain decision support much more easily (Zhang, 2013; Weymann et al., 2013). When the M-Health information does satisfy users' demands

Table 2. Definitions of relevant constructs

Constructs	Definitions	References
Health information Matching	The extent to which the MHI posted by M-Health platforms appeals to users or caters to users' preferences	(Tam & Ho, 2005)
M-Health Platform Credibility	The extent to which the M-Health platform providing health information is perceived to be believable, competent, and trustworthy by health information recipients	(Bhattacherjee & Sanford, 2006)
Cognitive Attitude	Individuals' beliefs, thoughts and values related to the object, and the degree to which users believe that accessing MHI for health management through M-Health apps is wise, beneficial and valuable	(Kay, 1993) (Aghakhani et al., 2018)
Trust in MHI	Whether users believe that the health information provided by M-Health apps is reliable and risk-free or whether it will have intangible benefits for their health management	(Doney & Cannon, 1997) (Huo et al., 2018)
Health Concern	Individuals' concerns or fears about potential disease risks, reflecting the degree to which an individual is worried or stressed that potential disease may have unintended negative consequences for his/her health	(Marakhimov & Joo, 2017)
Health Behavior Changes	An individual's experience of changes in health-related behaviors	(Ruggiero et al., 2011)

and is consistent with users' health conditions, it is easier for users to change their attitudes and behavior by utilizing the recommended MHI.

Thus, we hypothesize that:

H1: In the context of M-Health services, information matching is positively associated with an individual's health behavior changes.

In this study, platform credibility indicates that an M-Health platform as the source of health information is credible. Source credibility has been widely adopted as an indicator of individuals' behavioral outcomes in various domains, such as IT adoption behavior (Meng et al., 2019; Huo et al., 2018), and e-healthcare website behavior (Koo et al., 2014). First, a platform that is considered credible arguably has sufficient expertise to provide users with professional information; second, a platform that is considered credible can be trusted to provide high-quality information (Cheung et al., 2008). These two points are crucial for the healthcare domain because patients have higher needs for professional information than they may in other domains. This also suggests that the credibility of the platform where health information is obtained can make health information more persuasive to the user (Huo et al., 2018) and then may prompt them to act according to the health information advice (Jones et al., 2003). That is to say, a credible platform is highly effective in persuading individuals to make a health behavior change.

Thus, we hypothesize that:

H2: M-Health platform credibility has a positive effect on health behavior changes.

Mediating Effects of Attitudes

According to the theoretical basis of the ELM, the central and peripheral cues will also first impact individuals' attitude formations to achieve the persuasion effect (Petty & Cacioppo, 1986), thus further influencing their behavior intentions (Bhattacherjee & Sanford, 2006). In this case, these persuasive cues (i.e., information matching and platform credibility) may also indirectly impact individuals' healthy behavior changes through their attitudes toward MHI. Existing research also indicated that attitudes often mean individuals' inner acceptance of a target or object, which was an important pre-factor of follow-up behavior changes (Yang & Yoo, 2005).

As suggested by the ELM, two routes could channel the persuasive cues. Cognitive attitude refers to the values, thoughts, and beliefs for MHI as perceived by individuals (Aghakhani et al., 2018). Positive cognitive attitude indicates the degree to which users believe that accessing MHI through M-Health apps is wise, beneficial, and valuable for managing their health, resulting from individuals' objective cognitive processing health information. Existing research on information adoption also argued and reasoned that individuals adopt information was based on their beliefs and evaluation of consequences after adoption in some way (Sussman & Siegal, 2003). It has also been deemed as a significant predictor of several health-promoting behaviors or health-risk behaviors (Lawton et al., 2009).

Given the knowledge challenge in processing healthcare information, it is also likely that persuasive cues trigger the peripheral route to change users' health behavior. Trust refers to the user's belief or faith in the degree to which health information's content can be reliable and risk-free to their health management, serves the purpose of eliminating users' perceived uncertainty and security threats to mobile services (Gao et al., 2008). Particularly, in the health information context, trust is the result of quality assurance of the health information (Ding & Huang, 2020). Once users develop trust with the health information provided by MHI, trust becomes an alternative mechanism to cognitive attitude for persuasion. That is to say, users with a high level of trust in MHI will be more likely to consider that MHI can be used as a reference and guide for health self-management.

Therefore, we propose the following hypotheses:

H3a: The cognitive attitude mediates the relationship between information matching and behavior changes.
H3b: The cognitive attitude mediates the relationship between platform credibility and behavior changes.
H4a: The trust mediates the relationship between information matching and behavior changes.
H4b: The trust mediates the relationship between platform credibility and behavior changes.

The Moderating Effects of Health Concern

ELM not only specifies two routes for persuasion, but also suggests the individual differences in persuasion. Involvement or perceived relevance affects whether central or peripheral route is engaged in persuasion (Gu et al., 2017). In this context, health concern refers to individuals' concerns or fears about suffering from potential disease risks (Marakhimov & Joo 2017) and acts as a stressor to stimulate individuals to be alert with more perceived threat and motivated to engage coping (Boss et al., 2015).

Individuals differ in their health concerns depending upon many reasons, e.g., their actual health status, healthcare knowledge and etc. If individuals express higher levels of the health concern, they are more likely to rely on the central cues or more convincing cues (information matching in our context) rather than simple peripheral cues (platform credibility) when they change their beliefs and attitudes toward health information. Prior studies have also found that under high levels of the health threat, people are more inclined to rely on central persuasion cues to change their attitudes (Huo et al., 2018). In the same way, for individuals with a high level of health concern, their attitudes toward accepting health information would be more affected by information matching than platform credibility.

Therefore, we hypothesize that:

H5: Health concern enhances the positive relationship between information matching and attitude (cognitive attitude and trust) towards MHI.
H6: Health concern weakens the positive relationship between platform credibility and attitude (cognitive attitude and trust) towards MHI.

RESEARH METHODOLOGY

Data Collection

This study adopted an online survey method to validate the hypotheses. The data was collected from users who have experience with M-Health services. Respondents who participated in the study were from all over China and were users of large-scale M-Health apps, and each of them would get an incentive of RMB 15. Table 3 shows the demographic characteristics of the participants and types of M-Health apps used by users in our samples, as mentioned in Section 2. The specific interface examples are shown in Figure 3 (see Appendix 1).

Moreover, to reduce the inherent influences of individual characteristics on the dependent variables, age, gender, education, chronic-illness experience, and work condition were also used as control variables. Finally, we received 236 valid responses from 357 online questionnaires, representing a validity rate of 66%, which is considered good validity (Baruch & Holtom, 2008).

Instrument Development

The measurements used in this study were constructed by adapting previously validated instruments and rewording the items to fit to the study context. This study measured behavior changes through a composed variable (Ruggiero et al., 2011). Specifically, six yes/no questions about health behaviors were included in the questionnaire. Then, to obtain the dependent variable, we calculated the sum of ‘yes’ responses to these six items, so this sum could have a value from 1 to 6. Our measure of information matching was based on the instrument developed by Tam and Ho (2005). Our measures of platform credibility were adapted from Bhattacherjee and Sanford (2006). Cognitive attitude was measured with three items adapted from Kay (1993). Trust in MHI was measured with three items developed by Doney and Cannon (1997) and Huo et al., (2018) and suitable for the context of this study. Our measurement of health concern was adapted from the instrument developed by Marakhimov and Joo (2017), which measured perceived health risk related to wearable healthcare devices. A seven-point Likert scale was used to measure all items for the latent variables (1=strongly disagree; 7=strongly agree). The definition and detail measurements were shown in Table 2 and Appendix 1, respectively.

Table 3. The descriptive statistics of sample characteristics

Variables	Items		Number	Percentage
Age	<40		188	79.6%
	40-50		41	17.3%
	50-60		6	2.5%
	>60		1	0.4%
Gender	Male		109	46.1%
	Female		127	53.8%
Education	Senior high school		4	1.6%
	Technical secondary school		12	5%
	Junior college		36	15.2%
	Bachelor’s degree		159	67.3%
	Master’s degree or above		25	10.5%
Working	Yes		222	94.4%
	No		13	5.5%
Chronic Illness	Yes		79	33.4%
	No		157	66.5%
M-Health Platforms	The MHI source is certified by physicians	haodf.com	57	24.1%
		guahao.com	21	8.8%
	The MHI source is certified by platforms	chunyuyisheng.com	51	21.6%
	The MHI is integrated from multiple sources	xywy.com	38	16.1%
		xingren.com	3	1.2%
		jk.cn	61	25.8%
		Others	5	2.1%

DATA ANALYSIS AND RESULTS

For data analysis, we first analyzed the variables’ normality using the Kolmogorov-Smirnov test. The p-values are less than 0.05, indicating that the variables are non-normally distributed (see Table

Table 4. Correlations and discriminant validity

Construct[a]	Cronbach's α	CR	AVE	IM	PC	CA	TRU	CON	BC
IM	0.81	0.88	0.64	0.80					
PC	0.68	0.80	0.51	0.53	0.71				
CA	0.75	0.85	0.66	0.50	0.48	0.81			
TRU	0.76	0.86	0.67	0.56	0.51	0.59	0.82		
CON	0.80	0.87	0.69	0.10	0.19	0.10	0.16	0.83	
BC	1.00	1.00	1.00	0.32	0.20	0.29	0.34	0.12	1

[a]Notes: IM: Information Matching; PC: Platform Credibility; CA: Cognitive Attitude; TRU: Trust; CON: Health Concern; BC: Behavior Change

10 in Appendix 2). Given the variance-based SEM (structural equation modeling) enables the use of nonnormal data and small sample sizes (Shiau & Chau, 2016; Ringle et al., 2012), Smart PLS3.0 was used to perform SEM. It involves two stage analysis, i.e., measurement and structural model tests.

Measurement Model

To evaluate the reliability and convergent validity of constructs, we first calculated the Cronbach's α(>0.6), composite reliability (CR) (>0.7), average variance extracted (AVE) (>0.5), and factor loading (>0.7) (Straub et al., 2004; Fornell & Larcker 1981). As indicated in Table 4, all values of Cronbach's α, CR and AVE exceeded the cut-off criterion. All factor loadings are higher than 0.7 (except platform credibility is 0.66) (see Table 7 in Appendix 2), which indicated well-constructed reliability and convergent validity overall. To examine discriminant validity, we assessed cross-loading and the square roots of each construct's AVE (Straub et al., 2004). The principal diagonal elements in Table 4 represent each construct's AVE's square roots, and the lowest value (0.71) are higher than the maximum of 0.59 between TRU and CA. Cross Loadings, as shown in Table 7 (see Appendix 2), are also diacritical. Finally, all parameters in heterotrait-monotrait (HTMT) analysis, as shown in Table 8 (see Appendix 2), are lower than 0.85. Therefore, the assessment results verify that our measurement scale has satisfactory divergent validity.

Common Method Bias Testing

To check for common method bias, we followed Harmon's one-factor method (Harman, 1976) to detect this issue. Seven factors are presented, and the first unrotated factor only explains 23.14% of the covariance in this study, suggesting that no single factor accounts for the overall covariance of all the constructs. In addition, following a method suggested by Rönkkö & Ylitalo (2011), we included a marker variable to test for common method bias (Chin et al., 2012). We use three items that have low correlation with the items in this study to measure the marker variable. The results showed that the marker variable had no impact on trust, cognitive attitude and behavior changes, and the hypothesized relationships had no significant differences regardless of whether the marketer variable was introduced into the model, which indicates that the common bias does not pose a severe concern in this study (W.-L. Shiau et al., 2020).

Structural Model

In this section, we report the structural model results based on hierarchical regression, and details of regression results are shown in Table 5. The results show that control variables are insignificant. Second, both information matching and platform credibility are found to affect attitudes (cognitive attitude and trust) toward MHI. Additionally, information matching has a significant positive effect on

Table 5. Regression results of the hypothetical models

Hypothesis	Model 1		Model 2		Model 3	
	Coef.	T value	Coef.	T value	Coef.	T value
Age®BC	-0.076	1.066	-0.113	1.631	-0.113+	1.639
Gender®BC	0.061	0.951	0.057	0.919	0.057	0.943
Education®BC	0.012	0.173	-0.004	0.052	-0.004	0.051
Work®BC	0.055	0.866	0.054	0.792	0.054	0.817
Chronic®BC	-0.139*	2.042	-0.127	1.876	-0.127	1.858
IM®BC			0.202**	2.864	0.200**	2.818
PC®BC			-0.054	0.609	-0.047	0.538
CA®BC			0.095	1.055	0.095	1.081
TRU®BC			0.195*	2.473	0.190*	2.363
IM®CA			0.349***	4.906	0.364***	4.834
IM®TRU			0.406***	4.567	0.417***	4.618
PC®CA			0.293**	3.215	0.298**	3.256
PC®TRU			0.292***	3.547	0.295**	3.486
IM*CON®CA					-0.148*	2.063
IM*CON®TRU					-0.0994	0.987
PC*CON®CA					0.147+	1.611
PC*CON®TRU					0.137+	1.652
R2(CA)			0.316		0.372	
R2(TRU)			0.376		0.440	
R2(BC)	0.020		0.165		0.165	
+ P<0.10, * P<0.05, ** P<0.01, *** P<0.001; All the p-values are for two-tailed tests						
[b]Bold type indicates the hypothesis is supported						

health behavior changes, however, the platform credibility has no significant direct effect on behavior changes, hence H1 is supported and H2 is not supported. Third, we find that only trust in MHI has a significant positive effect on behavior changes, and the relationship between cognitive attitude and behavior changes is insignificant.

In Model 3, health concern significantly moderates the relationship between information matching and cognitive attitude, but it is negatively significant; and health concern marginally moderates the relationships between platform credibility and attitudes (cognitive attitude and trust), and it is positively significant; thus H5 and H6 are not supported. The moderation plots are shown in Figure 4 (see Appendix 1).

Mediation Test

Furthermore, following Zhao et al. (2010),we also test the mediating effect of attitudes (cognitive attitude and trust). As presented in Table 6, the results show that the indirect effects of information matching and platform credibility on behavior changes through trust ($a \times b$) is significant (β=0.077, t=2.033; β=0.055, t=1.966), and cognitive attitude has no mediation effects. Hence H3a and H3b are not supported, H4a and H4b are supported. Additionally, the direct effect of information matching

Table 6. Structural model assessment for mediating effect

Effects	Std β	*t*-value	Decision
Direct effects			
IM®CA	0.349	4.723***	
PC®CA	0.293	3.168**	
CA®BC	0.095	1.063	
IM®BC	0.200	2.746**	
PC®BC	-0.047	0.530	
IM®TRU	0.406	4.595***	
PC®TRU	0.292	3.604***	
TRU®BC	0.190	2.386*	
Indirect effects			
IM®CA®BC	0.033	0.995	Direct-only (Non-Mediation)
PC®CA®BC	0.028	1.008	No-effect (Non-Mediation)
IM®TRU®BC	0.077	2.033*	Complementary (Mediation)
PC®TRU®BC	0.055	1.966*	Indirect-only (Mediation)
Note(s): *p < 0.05; **p<0.01; ***p < 0.001			

on behavior changes (c) is significant (β=0.2, t=2.746), operating in the same direction with indirect effect ($a\times b\times c$ is positive). According to the mediation classification of Zhao et al. (2010), it indicates that trust is a complementary mediator between information matching and behavior changes. Similarly, since the direct effect of platform credibility on behavior changes is nonsignificant (β=-0.047, t=0.530), trust is an indirect-only mediator between platform credibility and behavior changes. Such results also explain why H2 is not supported.

DISCUSSION

Theoretical Implications

First, the results show that health information matching and platform credibility significantly affect cognitive attitude and trust in MHI. These findings are similar with prior studies' results (Huo et al., 2018; Mun et al., 2013; Aghakhani et al., 2018). It implicates that identifying the content and platform factors that influence users' attitudes toward MHI is critical. Such findings also contribute to M-Health and health information acceptance literature by explaining how these drivers persuade users to accept MHI from the perspective of ELM.

Second, information matching significantly influences behavior changes while platform credibility has an insignificant effect on behavior changes. To better understand this insignificant effect, we also tested the mediating effect of attitudes, which confirmed that the effect of platform credibility on health behavior changes is mediated by the user's trust in MHI, but did not find significant mediation effects of the cognitive attitude. This finding indicates that the decision-making for individuals to change health behaviors is determined by promoting individuals to form trust in MHI, rather than changing individuals' cognitive attitude. The reason for this result may be the individual's prudence in self-health management. Considering the uncertainty of mobile health information (e.g., inaccurate content, unclear source, uncertain effect on health or the effect might not live up to expectations), people are more likely to change health behaviors only when they perceive health information to be credible or risk-free for their health management, rather than when they perceive health information to be useful or valuable. Such results also provide new insights for clarifying the process mechanism by which MHI influences health behavior changes, and contribute to the M-Health literature through identifying drivers of health behavior changes from the ELM perspective. Additionally, as the effect of COVID-19 grows, research on distribution of epidemic health information on mobile information system (IS) and its impacts on public behaviors will remain important (W.-L. Shiau et al., 2021). Our results also provide some new insights on how effectively disseminate public health information on epidemic prevention through M-Health platforms, persuading individuals to engage in protective behaviors.

Third, the moderating effect of health concern on the relationship between M-Health information matching and cognitive attitude is negatively significant, contrary to the original ELM-based hypothesis. Specifically, Petty et al. (1981) suggested that the way in which elaboration likelihood moderates the effects of the central route and the peripheral route is grounded in the individuals' rational selection behavior. However, when people have high health concern, their behavior may be more irrational, which may motivate them to process peripheral information, such as platform credibility in this study. The managerial moderating effect of health concern on the effect of platform credibility also supports this line of thinking.

Thus, this study contributes to the ELM literature through expanding the theoretical boundary of elaboration likelihood.

Practical Implications

This study provides several insights for information recommendation design in M-Health. First, to encourage users to change daily health behaviors, M-Health platform owners should enhance the personalized recommendation level and credibility of MHI. For example, platform designers could develop an evaluation system to control the overall health information quality and trustworthiness or scientificity. Second, to attract more users to accept health information, operators need to pay more attention to the credibility of platform, and consider improving the popularity and reputation of platforms, rather than ignoring it. Third, consider the importance of accurate health information flow in health management, W.-L. Shiau et al. (2021) also proposed that information community is an important way to reduce information divergence and uncertainty. Thus, M-Health platforms can improve the trustworthiness of health information by establishing the health information community, reducing people's perceived risk and promoting their behavior changes. Finally, practitioners can utilize psychological characteristics of health concerns to guide M-Health platform design to increase users' satisfaction in their engagement with the platform. For instance, the platform could detect a user's health concern and incorporate it into the development of the recommendation algorithm. However, designers should take care to avoid overdoing users' health concern levels.

Limitations and Future Research

There are several limitations to our research. First, this study merely tests the mediating effects of cognitive attitude and trust. Some of those effects were verified, and one was partially rejected. Future studies would benefit from exploring other mediators, which would allow researchers to clarifying the process mechanism by which MHI influences health behavior changes.

Second, we only consider the factors related to health information and platforms, ignoring factors related to physicians and their expertise. Physicians, as the primary publishers of health information in M-Health apps, are also factors that influence users' determinations of health information quality. Therefore, future studies can introduce these related factors into the model, further investigate their impacts.

Third, our data were collected from an online survey, and all participants were from China, which also limits the applicability of our results. Thus, future research could collect data across different countries randomly and include some national culture factors.

CONCLUSION

Although it is established that M-Health apps have potential utility for promoting health management and improving health, studies on how specific MHI in the M-Health affect users' health behavior changes are rarely conducted. To further understand how to make MHI more persuasive, we apply ELM to explore the effects of health information matching and platform credibility on attitudes and health behavior changes. To a certain degree, our study introduces fresh insights applicable to information recommendation design in M-Health, rendering MHI more conducive to promoting patients' health behaviors and maximizing its service value.

DISCLOSURE STATEMENT

The authors reported no potential conflict of interest.

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ENDNOTE

1 Statista, Oct 22, 2020 "Global mobile medical apps market forecast 2025," [Online]. Available: https://www.statista.com/statistics/877758/global-mobile-medical-apps-market-size/

APPENDIX A

Figure 2. Measurements Items

Health Information Matching

1. The health information offered by this app is my preference.
2. The health information offered by this app is good.
3. The health information offered by this app is my favorite.
4. I think the health information offered by the app is what I want.

Platform Credibility

5. The app providing health information is knowledgeable on this topic.
6. The app providing health information is trustworthy.
7. The app providing health information is credible.
8. The app providing health information appears to provide expert knowledge on this subject.

Cognitive Attitude toward MHI

1. The health information in the app would help me to manage my health.
2. The health information in the app would help me to gain health management knowledge.
3. The health information in the app would help me to improve my daily exercise and to maintain a healthy diet.

Trust in MHI

1. I believe in the health information provided by the mobile app.
2. I trust the health information in the mobile app keeps our health benefits in mind.
3. The health information in the mobile app is trustworthy.

Health Concern

1. In relation to the possibility of potential diseases, my health condition is risky.
2. Given the potential of associated disease risks, my health condition is risky.
3. In general, potential disease could be associated with my health risks.

Behavior Change

In which of the following ways, if any, did the pushed health information you found in the mHealth app affect your own health care routine or the way you care for someone else? Did the information you found in the M-Health app.......（Yes or No）

1. Affect a decision about how to treat an illness or condition?
2. Change your overall approach to maintaining your health or the health of someone you help take care of?
3. Change the way you cope with a chronic condition or manage pain?
4. Affect a decision about whether to see a doctor?
5. Lead you to ask a doctor new questions, or to get a second opinion from another doctor?

Change the way you think about diet, exercise, or stress management?

Figure 3. Examples of MHI service module in different M-Health platform (Source: www.haodf.com; www.chunyuyisheng.com)

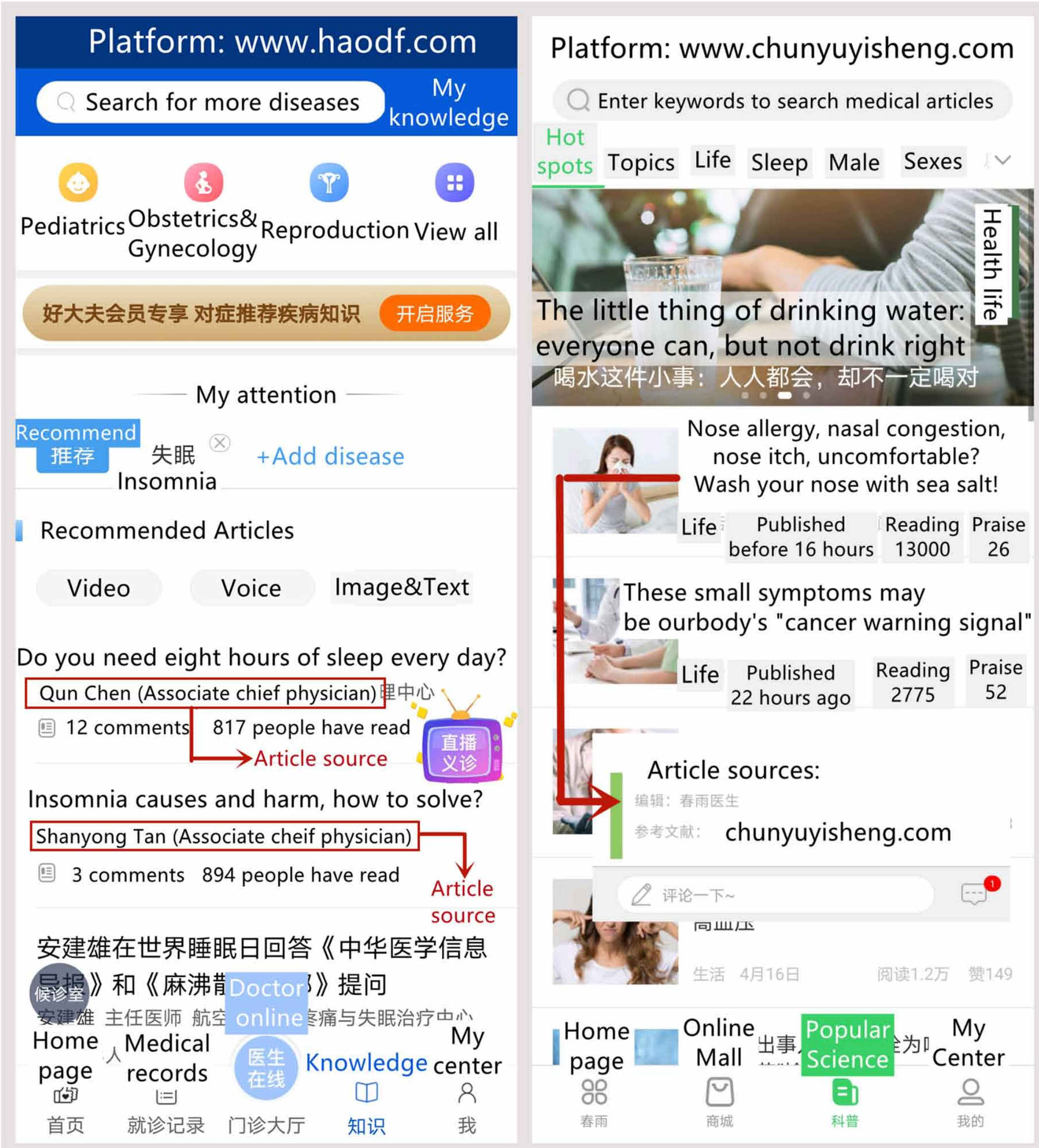
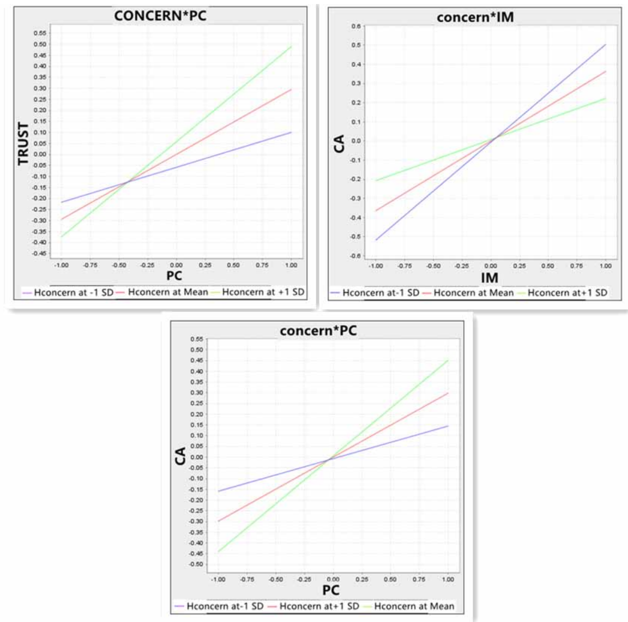


Figure 4. Plots of Moderating Effects



APPENDIX B

Table 7. Factor loadings and Cross loadings

Items[a]	CA	IM	PC	TRU	CON
CA1	0.84	0.46	0.42	0.53	0.06
CA2	0.80	0.44	0.36	0.50	0.04
CA3	0.81	0.34	0.38	0.43	0.15
IM1	0.40	0.78	0.45	0.39	0.10
IM2	0.46	0.78	0.47	0.49	0.06
IM3	0.40	0.82	0.40	0.43	0.08
IM4	0.35	0.82	0.37	0.47	0.08
PC1	0.34	0.35	0.73	0.35	0.14
PC2	0.29	0.39	0.73	0.44	0.23
PC3	0.40	0.36	0.73	0.36	0.09
PC4	0.34	0.41	0.66	0.29	0.07
TRU1	0.45	0.46	0.37	0.82	0.12
TRU2	0.58	0.48	0.42	0.82	0.16
TRU3	0.43	0.44	0.46	0.82	0.10
CON1	0.11	0.09	0.16	0.19	0.95
CON2	0.07	0.14	0.15	0.09	0.84
CON3	0.04	-0.02	0.20	0.06	0.69

Table 8. Results of the HTMT analysis

	CA	BC	CON	IM	PC	TRU
CA						
BC	0.336					
CON	0.113	0.117				
IM	0.644	0.360	0.123			
PC	0.674	0.247	0.268	0.716		
TRU	0.787	0.384	0.174	0.711	0.705	

Table 9. Results of Nonresponse Bias Testing

Construct	Significant Difference Between Two Groups of Samples[b] (The first 10% and last 10% of the samples)	
	T Value	**P Value**
Health Information Matching	-0.269	0.737
Platform Credibility	0.226	0.74
Cognitive Attitude	0.590	0.734
Trust in MHI	1.077	0.316
Health Concern	0.401	0.117
Behavior Change	0.696	0.836
[b]There is no significant difference between the samples, which indicates that sample selection bias is not present in this study (Podsakoff et al., 2003)		

Table 10. Results of Multivariate Assumption testing (Kolmogorov–Smirnov test (N=236))

Parameter [a,b]				Extreme difference			
Items	Mean	S.D.	Absolute	Positive	Negative	K-S Z	Sig. (2-tailed)
IM1	4.89	1.372	.171	.105	-.171	.171	.000[c]
IM2	5.40	1.256	.193	.117	-.193	.193	.000[c]
IM3	5.12	1.338	.189	.111	-.189	.189	.000[c]
IM4	5.09	1.367	.186	.113	-.186	.186	.000[c]
PC1	5.67	1.024	.245	.170	-.245	.245	.000[c]
PC2	5.56	1.023	.201	.174	-.201	.201	.000[c]
PC3	5.41	0.949	.238	.178	-.238	.238	.000[c]
PC4	5.44	1.167	.211	.137	-.211	.211	.000[c]
CA1	5.52	1.058	.210	.154	-.210	.210	.000[c]
CA2	5.55	1.138	.210	.146	-.210	.210	.000[c]
CA3	5.42	1.343	.208	.120	-.208	.208	.000[c]
TRU1	5.31	1.130	.233	.153	-.233	.233	.000[c]
TRU2	5.68	1.042	.243	.164	-.243	.243	.000[c]
TRU3	5.36	1.134	.212	.157	-.212	.212	.000[c]
CON1	5.00	1.396	.204	.144	-.204	.204	.000[c]
CON2	5.03	1.379	.224	.123	-.224	.224	.000[c]
CON3	5.26	1.346	.212	.131	-.212	.212	.000[c]
BC	4.48	1.260	.182	.127	-.182	.182	.000[c]
[a] Test distribution is normal. [b] Calculated from data. [c] Ripley's significance correction.							

Jinjin Song is currently working toward the Ph.D. degree in management with the Harbin Institute of Technology, Harbin, China. Her research interests include the area of M-Health, participation behaviors in online healthcare communities. Her research work has been published in journals, including the Telemedicine and e-Health.

Yan Li is currently working toward the Ph.D. degree in information systems with the City University of Hong Kong, Hong Kong, and the Harbin Institute of Technology, Harbin, China. Her research interests include the area of health care IT, hospital information systems, and knowledge management in online health communities. Her research work has been published in journals, including the Journal of Medical Internet Research.

Xitong Guo received the Ph.D. degree in information systems from the City University of Hong Kong and the Ph.D. degree in management science and engineering from the University of Science and Technology of China, in 2010. He is currently a Professor of information systems with the Harbin Institute of Technology. His current research focuses on big data and business analytics. His work has been published in peer-reviewed journals, including MIS Quarterly, Journal of Management Information Systems, ACM Transactions on Management Information Systems, and the European Journal of Information Systems.

Kathy Ning Shen received a Ph.D. degree in information systems from the City University of Hong Kong, in 2007. She is currently an Associate Professor at the UAE University. Her current research focuses on human-computer interaction virtual communities, online consumer behaviours, knowledge management, IT investment and enterprise applications. Her work has been published in journals, including Journal of Business Research, Business Research Quarterly, Information Systems Journal, Expert Systems with Applications.

Xiaofeng Ju received a Ph.D. degree from the Harbin Institute of Technology. He is currently a Professor of business administration with the Harbin Institute of Technology. His work has been published in journals, including Journal of Applied Mathematics, China & World Economy, Information Processing & Management.