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e-Health/m-Health Adoption and Lifestyle Improvements: Exploring the Roles of Technology Readiness, the Expectation-Confirmation Model, and Health-Related Information Activities

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e-Health/m-Health Adoption and Lifestyle Improvements: Exploring the Roles of Technology Readiness, the Expectation-Confirmation Model, and Health-Related Information Activities

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Abstract

This purpose of this study was to investigate (a) the prevalence and patterns of e-health/m-health use in Hong Kong; (b) the activities that people engage in via health-related information platforms/apps; and (c) the roles that technology readiness, the expectation-confirmation model, and e-health/m-health activities play in predicting lifestyle improvement. Data were collected from a telephone survey, with a probability sample of 1,007 respondents aged 18 or above. Our results show that 47.2% of the respondents were regular users of e-health technologies, 23.2% were m-health users, and only 10.7% used wearables for health purposes. Among the six e-health/m-health activities identified, health tutorials and health information seeking were the most frequently used, followed by recording/monitoring and medical services. The least popular activities were reminders and sharing experiences. As expected, the component variables in the expectation-confirmation model, particularly confirmation and perceived usefulness, were the strongest predictors for lifestyle improvement. External factors, such as being older and innovative, the use of e-health/m-health activities for recording/monitoring, health tutorials, medical services, and sharing experiences, also had significant impacts. Theoretical and practical implications are discussed.

Word count: 177

Key words: e-health/m-health, expectation-confirmation model, technology readiness, health-related activities, lifestyle improvements

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Introduction

The Internet today influences every facet of society. With its ever-increasing speeds, it has started a revolution in the way humans interact and seek information, and, as a consequence, it has improved many humans' quality of life. The rapid evolution of information sharing and communication exchange over the last few decades via the Internet has had a profound impact on the way people seek health-related information online. The Internet is flooded with health information that is accessible anytime by anyone with a mobile device, such as a smartphone or tablet. Researchers from all over the world are scrambling to study this phenomenon, seeking to contribute to the current body of knowledge in the field of m-health (e.g., Fox & Duggan, 2012). However, in a city with one of the world's highest mobile subscriber penetration rate of 228.3% and an Internet adoption rate of 79% in 2016 (Census and Statistics Department, 2016), little is known regarding the e-health/m-health adoption patterns in Hong Kong.

Generally, e-health refers to the seeking of health information via desktop or laptop computers, while m-health refers to the use of mobile communication technologies to access health services and information. In the field of public health research, m-health interventions have been developed to prevent obesity, smoking, and alcohol consumption, as well as to manage chronic diseases for patients (e.g., Burke et al., 2012). Although its effectiveness in improving healthy lifestyles has been demonstrated in previous studies (e.g., Ainscough et al., 2016), it is difficult to generalize these findings to the general population, as the focus of these studies have been highly customized for patients with specific needs and the use of certain utilities has been supervised by professional healthcare providers. Therefore, the current study goes beyond traditional healthcare practices in clinical settings and discusses the use of e-health and m-health technologies by the general public. Specifically, we focus on health-related information platforms and apps that are commercially available on mobile devices, as these health technologies can be easily accessed by a larger and much more diverse population.

There are several classic theories for examining how information and communication technologies ICTs become known, evaluated, accepted, and reevaluated, including the diffusion of innovation theory (DoI; Rogers, 1995), the technological acceptance model (TAM; Davis, Bagozzi, & Warshaw, 1989), and the theory of planned behavior (TPB; Ajzen, 1991). Although these theories provide varying explanations of consumers' acceptance behaviors, none of them can single-handedly explain the phenomenon of "acceptance-discontinuance anomaly"—when a consumer discontinues his or her use of the ICT after the initial adoption (Bhattacherjee, 2001, p. 351). Accordingly, by focusing on the post-consumption stage, Bhattacherjee (2001) proposed using the expectation-confirmation model (ECM) to explore how cognitive beliefs and affects shaped by users' own experiences can influence their continuance intentions. Based on this original model, Lin and Bhattacherjee (2007) suggested future studies to consider external variables that may influence consumers' beliefs, emotions, and use intentions. Thus, technology readiness—a disposition toward embracing new technologies—is integrated into the ECM in this study. We believe that when users feel optimistic, innovative, comfortable, and safe regarding a health-related communication technology, they are more likely to perceive it as useful, confirm their initial expectations, and foster a feeling of satisfaction and continuance intentions. In addition to the affective (satisfaction) and cognitive (continuance intention) outcomes, we also believe that the sustained use of health-related information platforms and apps to develop and maintain a healthy daily routine (such as exercising more, increasing the quality of one's sleep, and eating more fruits and vegetables) can improve healthy lifestyles.

Although the ECM has been applied to various information system (IS) use contexts to predict users' continuance behaviors, no study, to the best of our knowledge, has yet attempted to incorporate technology readiness and activities in e-health/m-health information platforms/apps into the original model to predict lifestyle improvement. Thus, this exploratory study attempts to expand the scope of consumer behavior research and contribute to the extended theorization of ECM. More specifically, this study aims to investigate (a) the prevalence and patterns of e-health/m-health use behavior in Hong Kong; (b) the activities engaged in when using the health-related information platforms/apps, and (c) the roles of technology readiness, the expectation-confirmation model, and e-health/m-health activities in predicting lifestyle improvement.

Literature Review

The Expectation-Confirmation Model

Drawing on the expectation-confirmation theory (Oliver, 1980), Bhattacherjee (2001) proposed the ECM to evaluate the relationships among post-consumption belief, affect, and intention in IS use. Different from the DoI theory (Rogers, 1995), the TAM (Davis, Bagozzi, & Warshaw, 1989), and the TPB (Ajzen, 1991), the ECM only examines post-consumption variables that may motivate individuals to continue using an IS. Generally, there are three key components in the model: confirmation of expectations, perceived usefulness (PU), and satisfaction. The ECM posits that high PU and confirmation can foster a feeling of satisfaction after IS use, thus increasing continuance intentions in the future (Bhattacherjee, 2001).

As a dependent variable in the ECM, continuance intentions refer to the tendency to continue using an IS after initial acceptance. It should be noted that adoption intention and continuance intention are two different aims in technology use. Forming adoption intention is more important in the pre-consumption stage, whereas continuance intention carries more weight in the post-consumption phase. Of the three key predictors, level of satisfaction is viewed as the primary factor that can influence users' continuance intentions (Bhattacherjee, 2001). According to Oliver (1996), satisfaction is conceptualized as an emotion-based response to an IS. It is a subjective evaluation of whether the product or service used provided a pleasurable level of consumption-related fulfillment.

Furthermore, users' satisfaction is influenced by two cognitive factors: confirmation of expectations and PU. Specifically, confirmation of expectations refers to the evaluation process, during which users' initial expectations are confirmed during actual use (Bhattacherjee, 2001). When the original expectation is met or exceeded, consumers are likely to foster a positive feeling toward the new technology. In addition, PU is understood as a utilitarian evaluation of an IS (Bhattacherjee, 2001). If the technology helps users improve their performance, it is usually perceived as useful. Compared to the affective component embedded in satisfaction, PU captures the instrumentality of IS usage. The more PU users have, the more likely they are to be satisfied with the technology.

Besides these main relationships, the ECM also predicts that (a) the extent of confirmation can influence PU and (b) PU can directly determine continuance intentions (Bhattacherjee, 2001). The former relationship is proposed based on the cognitive dissonance theory (Festinger, 1962), which posits that users may experience cognitive dissonance if their usefulness perceptions formed in the pre-acceptance phase are disconfirmed in the post-acceptance phase. Rational users will then modify their perceptions toward usefulness so that they are more consistent with reality. This latter relationship is proposed due to the robustness of PU in predicting consumer behaviors irrespective of the type of IS and use stage (e.g., Davis, Bagozzi, & Warshaw 1989). Considering that IS use is often viewed as a means to obtain benefits or rewards, the utilitarian value of IS has become a significant predictor in both the pre-acceptance and post-acceptance stages. In summary, the ECM posits that consumers' continuance intentions are primarily determined by their satisfaction with the IS use and PU. This level of satisfaction is, in turn, influenced by their confirmation of expectations from prior IS use and PU. Furthermore, the PU is determined by the user's confirmation level.

As a popular model for predicting consumer behavior, the robustness of the ECM has been confirmed in various research domains, including online banking services (Susanto, Chang, & Ha, 2016), mobile travel booking service (Zhong, Lou, & Zhang, 2015), social networking sites (Oghuma et al., 2016), mobile advertising (Hsiao & Chang, 2014), paid mobile apps (Hsu & Lin, 2015), Internet Protocol TV (IPTV) (Lin et al., 2012), digital textbooks (Joo, Park, & Shin, 2017), and e-learning (Lee, 2010). However, in the field of e-health and m-health, the ECM has only been applied to few contexts, such as an m-health service study in Bangladesh (Akter, Ray, & D'Ambra, 2013) and a medical e-learning system study in Taiwan (Chou et al., 2012). Considering that health-related information platforms/apps are steadily gaining popularity, it is imperative to examine users' attitudes and behaviors in the post-acceptance stage. Thus, we have chosen to use the ECM as a theoretical guideline in this study, and we propose the following research hypotheses:

H1: Users' level of satisfaction with health-related information platforms/apps is positively associated with their continuance intention.

H2: Users' extent of confirmation is positively associated with satisfaction with health-related information platforms/apps use.

H3: Users' PU is positively associated with their (a) satisfaction with and (b) continuance intention of health-related information platforms/apps use.

H4: Users' extent of confirmation is positively associated with their PU of health-related information platforms/apps use.

Integrating Technology Readiness Into ECM

In addition to the three key variables in the ECM, Lin and Bhattacherjee (2007) suggested that future studies consider external variables that may shape users' beliefs, affects, and continuance intentions toward an IS. Therefore, we have incorporated the concept of technology readiness into the ECM. According to Parasuraman (2000), technology readiness refers to one's propensity to embrace new technology to achieve goals in one's home life and at work. It is a multifaceted construct that contains four dimensions: optimism (a positive perception toward technology and a belief that it provides people with increased control, flexibility, and efficiency in their lives), innovativeness (a tendency to become a technology pioneer), discomfort (a perceived lack of control over technology and a feeling of being overwhelmed by it), and insecurity (distrust of technology and skepticism about its ability to work properly). Of these, optimism and innovativeness serve as the key drivers of technology readiness. They encourage people to use new technology, and they foster perceptions of safety and novelty. In contrast, discomfort and insecurity are inhibitors of technology readiness. They make consumers reluctant to embrace new technology and generate feelings of anxiety, insecurity, and uncomfortableness.

Although health-related information platforms and apps are viewed as promising technologies that can promote health behavior change, users' technology readiness may influence its effectiveness, as some people are technology pessimists (Edison & Geissler, 2003) and others have a degree of technophobia (Meuter et al., 2003). Uncomfortable feelings toward health technologies may prevent these individuals from further use. Previous studies have linked technology readiness to users' satisfaction levels, as well as their behavioral intentions, in various technology adoption contexts, including self-service technology (Lin & Hsieh, 2006), e-insurance services (Taylor, Celuch, & Coodwin, 2002), and mobile services (Chen, Liu, & Lin, 2013). They consistently found that technology readiness is a significant driver of users' satisfaction and adoption intentions. However, these relationships have not been examined in the post-acceptance phase, especially in relation to e-health and m-health use. To fill this research gap, here we define technology readiness as a constant psychological factor that influences all three key variables in the ECM. Accordingly, we propose the following research hypothesis:

H5: Technology readiness is positively related to one's (a) extent of confirmation, (b) PU, (c) level of satisfaction, and (d) continuance intentions to use health-related information platforms/apps.

Engagement in e-Health/m-Health-Related Information Activities

There are several main activities for which people engage in health-related information platforms and apps on mobile devices. They include seeking health information; asking about medical services; sharing health-related experiences; setting reminders; recording, tracking, and self-monitoring; and attending health tutorials (e.g., Burke et al., 2012; Helander et al., 2014; West et al., 2013). Considering that a health-related platform or app is a powerful combination of various functionalities and information, two types of e-health and m-health activities are proposed in this study, namely information-based activities (e.g., health information seeking) and utility-based activities (e.g., self-monitoring).

Information-based activities are focused on content provided by health-related information platforms/apps. However, the overall content quality tends to be quite low, especially in m-health technologies. For example, Brunstein et al. (2012) analyzed the 100 top health and fitness apps for iPhone users and found that most apps only provided general information and assistance. They argued that the lack of substantive health information made it difficult for users to achieve healthier lifestyles after the initial adoption. Similarly, after analyzing 23 popular weight management apps in the Apple Store, Bardus et al. (2016) found that their information quality achieved the lowest score on the Mobile App Rating Scale. These findings indicate that the health information provided in most e-health and m-health platforms and apps is scattered, superficial, and uninstructive. Thus, it is postulated that it is difficult to utilize information-based activities to promote health behavior change.

In contrast, utility-based activities have been found to be significantly related to positive attitudes and health behaviors. For instance, Bardus et al. (2016) pointed out that users are generally satisfied with the functions provided by weight management apps, and they are more likely to use these apps when a tracking function is presented. Moreover, Burke et al. (2012) developed a 24-month m-health intervention to examine the relationship between dietary app use and weight loss, and they found that the self-monitoring functionality combined with daily feedback led to the largest amount of weight loss. In sum, these findings indicate that utility-based activities have the potential to influence users' lifestyle improvements.

Given that one goal of this study was to examine the activities that users engage in on health-related information platforms and apps, we proposed the following research question:

RQ1: What are the activities that users engage in on e-health/m-health-related information platforms/apps via desktop/laptop computers and mobile devices?

Lifestyle Improvements

Lifestyle improvements refer to changes in health behavior after the continued use of health-related information platforms/apps. Examples of lifestyle improvement include exercising more, changing bedtime habits, controlling diet and weight, and eating more fruits and vegetables. The emergence of e-health and m-health technologies offers a highly accessible and cost-effective way to promote health behavior changes. In addition, professional healthcare providers have developed many e-health and m-health intervention programs to help people break unhealthy habits (e.g., smoking) and monitor and treat severe diseases (e.g., HIV and breast cancer) (e.g., Allman-Farinelli et al., 2016; Dale et al., 2015; van Dijk et al., 2016). Among the various intervention procedures, adherence (i.e., sustainability) has been emphasized as it can influence the effectiveness of e-health and m-health interventions, thus determining the extent of health behavior change. For example, Allman-Farinelli et al. (2016) developed a weight management program for young adults in Australia, and they found that after the cessation of the 12-week intervention, young people who had sustained the healthy lifestyle lost more weight and were healthier. Similarly, van Dijk et al. (2016) provided a 6-month online coaching program for couples who were contemplating pregnancy or were already pregnant. They found that complete adherence to the intervention program increased nutrition intake and health behavior changes. Considering that lifestyle improvement is a significant concern of e-health and m-health adopters, we have postulated that users who form a continuance intention of using health-related information platforms and apps are more likely to experience lifestyle improvement, as health behavior change requires sustained use. Therefore, we have proposed the following hypothesis:

H6: Continuance intention to use health-related platforms/apps is positively related to lifestyle improvements.

Furthermore, grounded in the ECM (Bhattacherjee, 2001), in this study we have sought to expand the existing consumer behavior research by addressing the following research question:

RQ2: How do demographics, technology readiness, e-health/m-health activities, confirmation of expectations, PU, satisfaction, and continuance intention influence lifestyle improvements?

Method

Sample and Sampling Procedure

We conducted a telephone survey from November 25, 2016, to December 9, 2016, using a computer-assisted telephone interview system. A probability sample of over 3,052 telephone numbers in Hong Kong was drawn from the most updated edition of the telephone directory. Interviewers were trained undergraduate students, and all calls were made from a central location with close supervision. After excluding ineligible respondents, nonworking numbers, and numbers that were not answered after five attempts, the completion rate was 33%. The sample consisted of 47.6% males aged 18 or above. The median age category was 40 to 49 years, median education was Grade 10 to 12, and median monthly income was USD 3,866 to 5,155. Of the 1,007 respondents who successfully completed the survey, 187 did not indicate if they had or had not used e-health technologies to access health-related information on the Internet (see Table 1 for details). Of the remaining 820, 52.8% (n = 433) indicated that they never or rarely used e-health to obtain health-related information online. Of those who indicated that they had used e-health services, 47.2% (n = 387) were regular users (i.e., they sometimes, often, or very often sought health information via desktop or laptop computers). Similarly, 20.2% (n = 203) were m-health users (people who seek health information via platforms or apps on mobile devices such as smartphones or tablets), while only 9.6% (n = 97) used wearables for health purposes. Data analyses were based on e-health users, with N = 387.

(** Insert Table 1 Here **)

Measures

Expectation-confirmation. Three perceived confirmation items were modified and adopted from Bhattacherjee (2001) to confirm the benefits of health-related information seeking on e-health/m-health platforms and apps. Sample items included statements such as “My experience with using health-related information platform is better than what I expected.” Cronbach’s alpha was set at .88. The measurement items in the questionnaire are shown in Appendix A.

Perceived usefulness. To measure PU, three items modified from Davis, Bagozzi, and Warshaw (1989) and Bhattacherjee et al. (2008) were used. Sample items included “I find the use of health-related information platforms effectively improves my health condition.” Cronbach’s alpha was set at .78.

Satisfaction. Respondents were asked how much they agreed with the statement, “Regarding my overall experience when using health-related information platforms and apps, I am: (i) very satisfied, (ii) very pleased, and (iii) very content.” Cronbach’s alpha for the three items was high at .80.

Continuance intention. Continuance intention was measured with three items adapted from Mathieson’s (1991) behavioral intention (to accept IS) scale. Sample items included “I intend to keep using the health-related information platform that I currently use.” Cronbach’s alpha was at .74.

Technology readiness. A total of 12 items were adopted from Parasuraman (2000) and Yen (2005). For drivers of technology readiness, six items were used, including “Technology gives me more freedom and mobility” (for optimism) and “I often keep up with the latest technological development that I am interested in" (for innovation). Similarly, six items were used to assess inhibitors of technology readiness. Sample items included "The manual for a high-tech product or service is hard to understand" (for discomfort) and "It's not safe to pay online" (for insecurity). As shown in Appendix A, Cronbach's alphas for optimism, innovation, discomfort, and insecurity were .68, .71, .71, and .78, respectively.

Lifestyle improvement. Changes in health behaviors such as sleep problems were assessed. Respondents were asked how much they agreed with the following three statements: The use of health-related information platforms/apps (a) "helps my weight control," (b) "improves my sleep quality," and (c) "motivates me to walk more." The reliability alpha was acceptable at .75.

A 5-point Likert scale was used with 1 = strongly disagree and 5 = strongly agree for all the measures above.

e-Health/m-health activities. Items for e-health/m-health–related information activities were gathered from the literature (e.g., Lee, Choi, & Noh, 2016; Zhao, Freeman, & Li, 2016) and an in-depth interview/focus group soliciting functions and activities engaged in e-health/m-health platforms/apps by a group of six college students. Respondents were invited to evaluate 18 items on how often they used each of the functions on health-related information platforms and apps using a 5-point Likert scale ranging from "never" (1) to "very often" (5). Sample items for the information-based activity included "To search for information about a specific disease or medical problem." Items for utility-based activities included "To buy medicines or health-related products," "To share opinions on the medical products and services I purchased," "To remind myself when to take medicine," "To record and monitor the amount of exercise," and "To follow the exercise instructions."

Demographics. Gender, age, education, and income were also assessed.

Results

Activities on Health-Related Information Platforms/Apps

To answer RQ1, we used a principal components factor analysis using the Varimax rotation to examine 18 e-health/m-health activity items. This yielded six dimensions after we eliminated three items that failed to cluster or cross-load to other factors. As shown in Table 2, the eigenvalue was greater than 1.0; the means, standard deviations, and the variance are also reported in this table. The first factor, health information seeking (alpha = .67), included four items reflecting people's use of e-health/m-health platforms/apps to search for relevant information for a specific disease or health problem. The second factor, medical services (alpha = .63), included three items indicating people's use of e-health/m-health platforms/apps to pay medical bills, to buy medicines, or to make doctor appointments online. The third factor was sharing experiences (two items; alpha = .79); the purpose of this factor was to determine how people use e-health/m-health platforms/apps to share opinions on medical products or services and to share stories about personal health experiences. The fourth factor, reminders (two items; alpha = .72), showed that people use e-health/m-health platforms/apps to remind themselves when to take and refill medicines. The fifth factor was recording/monitoring (two items; alpha = .67), reflecting people's use of e-health/m-health platforms/apps to record and monitor their sleep quality and amount of exercise. The last factor was health tutorial (two items; alpha = .58), illustrating that people use e-health/m-health platforms/apps to seek information on diet, exercise, or fitness and to follow instructions for exercise routines.

Overall, the six factors successfully described the broad spectrum of e-health/m-health activities people generally engage in on various platforms and apps for health-related information and services. Despite the low reliability alphas on some dimensions (i.e., below the acceptable level of .70), we found that the most popular activities were utility-based health tutorials (M = 2.59, SD = .89) and information-based health information seeking (M = 2.57, SD = .72). The least popular activities were reminders (M = 1.21, SD = .58) and sharing experiences (M = 1.49, SD = .77).

(** Insert Table 2 Here **)

Hypotheses Testing

In H1, we hypothesized that users' levels of satisfaction with health-related information platforms/apps use are positively associated with their continuance intention. Our regression results in Table 3 show that satisfaction is a significant and positive predictor of continuance intention (β = .27, $p < .001$) in the use of health-related information platforms/apps. In H2, we proposed that the extent of confirmation is positively associated with satisfaction with health-related information platforms/apps use. Results in Table 3 indicate that confirmation significantly predicted satisfaction (β = .23, $p < .001$). In H3, we posited that users' PU is positively associated with their (a) satisfaction with and (b) continuance intention of health-related information platforms/apps use. The results in Table 3 reveal that PU is significant predictor of (a) satisfaction (β = .30, $p < .001$) and (b) continuance intention (β = .21, $p < .001$). And, in H4, we expected that the users' extent of confirmation was positively associated with their PU of the health-related information platforms/apps. Results in Table 3 shows that confirmation and PU were significantly linked ($\beta = .41$, $p < .001$). Therefore, H1, H2, H3a, H3b, and H4 were all fully supported.

In H5, we proposed that technology readiness is positively related to (a) the extent of confirmation, (b) PU, (c) level of satisfaction, and (d) intention to continue to use the health-related information platforms/apps. Results in Table 3 show that drivers of technology readiness (innovation: $\beta = .14$, $p < .01$; optimism: $\beta = .19$, $p < .001$) and inhibitors of technology readiness (discomfort: $\beta = -.13$, $p < .05$) were significant predictors of confirmation. Therefore, H5a was largely supported. The results also showed that technology readiness drivers, optimism in particular, significantly and positively predicted PU ($\beta = .18$, $p < .001$) and that the relationship between inhibitor discomfort and PU ($\beta = .09$, though at the $p < .1$ level) was also significant. Thus, H5b received some support. Similarly, discomfort was also a significant predictor of satisfaction ($\beta = .15$, $p < .01$). Therefore, H5c was marginally supported. Furthermore, results in Table 3 indicate that innovation and continuance intention were significantly and positively correlated ($\beta = .08$, $p < .05$). Thus, H5d received some support.

In H6, we hypothesized that continued intention to use health-related information platforms/apps was positively related to lifestyle improvements. However, contrary to what was expected, the regression results in Table 3 did not support this hypothesis ($\beta = -.06$, $p > .05$). Therefore, H6 was rejected.

(** Insert Table 3 Here **)

Predicting Lifestyle Improvements

To explore the influence of demographics, technology readiness, e-health/m-health activities, confirmation of expectations, PU, satisfaction, and continuance intention on lifestyle improvement, we conducted a multiple regression analysis. As shown in Table 3, as expected, our results showed that the component variables from the ECM were among the strongest predictors; e.g., PU ($\beta = .50$, $p < .001$) followed by confirmation ($\beta = .27$, $p < .001$). E-health/m-health activities such as recording/monitoring ($\beta = .11$, $p < .01$), health tutorials ($\beta = .08$, $p < .05$), medical services ($\beta = .08$, $p < .05$), and sharing experiences (negative: $\beta = -.07$, $p < .05$) were also significantly linked to lifestyle improvement. Technology readiness, innovation in particular ($\beta = .11$, $p < .01$), also had a significant influence on lifestyle improvement. The results also show that being older ($\beta = .12$, $p < .01$) was a significant factor in perceiving a better lifestyle as a result of using e-health/m-health platforms/apps. The amount of variance explained was 49%.

Conclusion and Discussion

e-Health/m-Health Penetration in Hong Kong

In general, we found that the adoption rate of health-related information platforms and apps among Hong Kong citizens was relatively low. Of the 820 respondents, only 47.2%, 20.2%, and 9.6% reported that they were regular users of e-health, m-health, and wearable devices, respectively. These results were consistent with Yan’s (2010) study, who found that only 44% respondents in Hong Kong could be identified as health surfers. Similarly, CNNIC (2017) also reported that at the end of 2016, there were 195 million e-health users in mainland China, which only accounted for 26.6% of all the netizens (i.e., Internet users).

Given that the fields of e-health and m-health were initiated in the late 1990s and early 2010s, respectively,[1] it is postulated that the low adoption rate may be due to the nascent status of e-health/m-health technologies. The public does not seem to be prepared to use them for health-related purposes.

e-Health/m-Health Activities

In this study, we identified six specific activities that people engage in when using health-related information platforms and apps, including one information-based activity (e.g., health information seeking) and five utility-based activities (e.g., medical services, sharing experiences, reminders, recording/monitoring, and health tutorials). Of the six types of activities, seeking medical services, sharing experiences, recording/monitoring, and using health tutorials were found to be significantly related to lifestyle improvements.

Factors Influencing Continuance Intention

This study has provided additional evidence to support the robustness of the ECM. As expected, confirmation, PU, and satisfaction were three critical factors that influence users' continuance intention of using health-related information platforms and apps. Considering that this study focuses on the newest functions featured in health-related information platforms and apps, technologies readiness and distinct e-health/m-health activities were purposively incorporated to enhance the model. The results show that innovation is a significant predictor of continuance intention. It indicates that keeping up with the latest technological developments, figuring out high-tech product and services, and being the first

[1] Mitchell (1999) was the first to propose the concept of "e-health." He pointed out that the rise of e-health indicated the death of telemedicine and medical informatics. Moreover, in 2011, WHO proposed a clear definition of m-health, which is generally considered to be the starting point for the m-health field.

to acquire new technology can foster users' intention to continue to use e-health/m-health technologies. This finding is consistent with previous studies that integrated technology readiness into the ECM. For example, Chen, Jong, and Lai (2014) found that the drivers (optimism and innovativeness) of technology readiness were positively related to continuance intention of using e-appointment systems. Moreover, Chen, Liu, and Lin (2013) combined the four facets of technology readiness in their measurement and found that technology readiness, as a composite, significantly influences consumers' intentions to continue using mobile services. Considering the important role of technology readiness in explaining consumer behaviors in the post-consumption stage, future studies are suggested to incorporate technology readiness into the ECM to more precisely predict users' continuance intention (Chen, Liu, & Lin, 2013).

However, contrary to what we expected, we found that no e-health/m-health activity can significantly predict users' continuance intention of using health-related information platforms and apps. One plausible explanation for this is that the effect of the activities was negated by the three key components in the ECM. Although a significant relationship between activities and continuance intention was not found, the findings show that some activities were positively related to the three key variables in the ECM (as shown in Table 3). For example, health information seeking was marginally but positively related to confirmation; sharing experience was significantly associated with PU; and health tutorial was positively linked to users' level of satisfaction. Thus, future studies are suggested to examine the possible moderating role of the ECM variables when exploring the relationship between activities and continuance intention.

Factors Influencing Lifestyle Improvement

In addition to continuance intention, lifestyle improvement was another important outcome related to e-health/m-health adoption. We found that PU, confirmation, innovation, optimism, e-health/m-health activities (specifically medical services, sharing experiences, recording/monitoring, and health tutorials), and age were significant predictors of lifestyle improvements. As expected, two key variables in the ECM were found to be the most robust predictors of lifestyle improvements. This indicates that perceiving e-health/m-health technologies as useful and confirming the expectation of the use were important factors that influenced lifestyle behavior changes. One possible explanation is that PU and confirmation of use are the cognitive components in the ECM, and both involve utilitarian evaluations of technology use experiences. If an individual’s experience with e-health/m-health platforms and apps can promote health behavior changes, they can be perceived and confirmed as useful. Given that lifestyle improvements are an outcome-oriented variable, it is reasonable to think that these two cognitive components of the ECM can significantly predict lifestyle improvements.

However, it is surprising to note that satisfaction and continuance intention failed to predict lifestyle improvements in our study. One plausible reason may be that lifestyle improvement is an outcome-oriented dependent variable. It emphasizes the positive health outcomes obtained from e-health/m-health use. However, satisfaction is an emotion-based response that focuses on the affective or pleasurable user experience rather than actual outcomes. Therefore, satisfaction did not predict lifestyle improvement in the e-health/m-health use context. With respect to continuance intention, this study also did not find a main effect on lifestyle improvement. However, as discussed earlier, it might exert differential effects on the formation of lifestyle changes or improvements through moderation of individuals' e-health/m-health activities. Future research should explore this possibility.

To extend the ECM, this study adopted technology readiness and e-health/m-health activities in the post-consumption context as predictors of lifestyle improvements. Our findings show that the drivers of technology readiness (innovation and optimism) had a significant positive influence on lifestyle improvement. This means that the higher the level of users' technology readiness is, the more likely they will have notable health behavior changes after adopting health-related information platforms and apps. This result may have important practical implications for e-health/m-health users. In order to generate positive health-related outcomes, it is wise for users to embrace new technologies and adopt an innovative and optimistic attitude toward health-related information platforms and apps.

With regard to activities, it is reasonable to accept that seeking medical services, recording/monitoring, and using health tutorials significantly and positively predict lifestyle improvements. This indicates that people who often use e-health/m-health technologies to pay medical bills; buy medicine; make doctor appointments, remind them when to take medicine and get a refill; record/monitor sleep quality; and seek tutorial information on diet, fitness, and exercise would experience greater lifestyle improvements in weight control and quality of sleep, as well as walk more. However, contrary to our expectations, sharing experiences was found to be a negative predictor of lifestyle improvement. This indicates that the more users share their health-related experiences online, the less likely they are to perceive that their lifestyle would be improved.

This finding seems to contradict common sense because sharing health-related experiences with others can be viewed as a positive self-rescue behavior that can help patients express their emotions as well as obtain online community support. However, previous studies found that writing expressively about a traumatic event may not necessarily lead to positive outcomes because the outcomes are generally contingent on the kind of emotions elicited (e.g., Lieberman & Goldstein, 2006; Pennebaker & Beall, 1986). For example, Pennebaker and Beall (1986) analyzed expressive writings from 177 participants and found that a higher use of positive words predicted a healthier life compared to the use of negative words. Lieberman and Goldstein (2006) examined the role of emotional expression in online support groups for 52 women with breast cancer and found that not all negative emotions were equal. Specifically, the greater expressions of (or discharge) anger were related to a higher level of quality and lower feeling of depression, whereas the greater expressions of fear and anxiety were associated with lower quality of life and higher depression.

Moreover, the expression of sadness was not significantly related to any physical or mental health benefits. Accordingly, sharing health-related experiences via health-related information platforms and apps may not necessarily contribute to lifestyle improvements, especially when permissive emotions are elicited by sharing behavior.

Furthermore, in this study, we have found that health information seeking and reminder setting are not significantly linked to lifestyle improvements. In fact, the insignificant relationship between health information searching and lifestyle improvements was expected as the quality of information available in current health-related information platforms and apps may be relatively low, especially when the information is presented in language full of medical jargons and non-user-friendly instructions. This appears to weaken the effect of health information seeking behavior on positive health-related outcomes. Moreover, the notion of “e-health literacy” can be applied to explain this insignificant relationship (Norman & Skinner, 2006). A previous study found that people with advanced e-health literacy skills may use more efficient online search strategies and identify health information with higher quality (Quinn, Bond, & Nugent, 2017). Thus, it is postulated that more benefits can be derived from their health information–seeking behavior. However, when this essential e-health literacy is lacking, health information searching may not necessarily contribute to lifestyle improvements as the identified information may be unreliable, irrelevant, unsophisticated, and low in quality.

In terms of the insignificant effect from reminder setting, one plausible explanation may be due to the demographic characteristics of the surveyed respondents. Given that our sample was primarily composed of middle-aged adults (median age category = 40–49) who self-reported that reminder setting was the least popular activity that they engaged in with m-health technologies, the participants may all have the perception that reminder setting is a behavior that is mainly practiced by old people who often forget their medicine schedule. This biased perception may reduce their use of the reminder function, thus dismissing its influence on lifestyle improvement.

Lastly, this study found that old people were more likely to perceive a greater health lifestyle change after using e-health and m-health technologies. This may be because old people are more health conscious compared with young people. Therefore, they attach greater importance to the use of health-related information platforms and apps and have higher expectations that the physical benefits would be obtained from e-health and m-health use.

Implications

Theoretically, the current study expands the current research to include the role that key components in the ECM play in lifestyle improvement by considering two “external variables” that may shape users’ beliefs, affects, and continuance intentions toward e-health/m-health technologies. The results reveal that both drivers and inhibitors of technology adoption are important factors that can significantly affect components of the ECM and ultimately behaviour changes to adopt a healthier lifestyle. Six types of activities were also included as post-consumption factors that have important practical implications for providers of e-health and m-health. Practically, the findings of our study suggest that providers should develop or strengthen the content and/or functions in their health-related information platforms and apps based on these six activities to facilitate users’ lifestyle improvements.

Limitations and Suggestions for Future Research

Several limitations should be noted in our study. The cross-sectional nature of the survey means that any potential causal relationships cannot be identified. For example, it is not clear whether lifestyle improvements were the cause or the outcome of continuance intention. Given that continuance intention was found to not be a significant predictor of lifestyle improvement but that these were significantly correlated at the bivariate level ($r = .40$, $p < .001$), it is reasonable to postulate that lifestyle improvement may be the cause of users’ continuance intentions. This means that users may foster the continuance intention of using health-related information technologies after they experience positive health behavior changes. However, to draw an accurate conclusion of the causal direction, multi-wave investigations are required in the future. Furthermore, given that our telephone survey was based on a randomly drawn sample from a fixed-line phone directory (with 94% penetration in Hong Kong), households that only use mobile phones may have been neglected. Accordingly, the findings of this study cannot be generalized to all mobile phone users as they may have greater opportunities to access various up-to-date health-related information platforms and apps. We suggest that future studies adopt multi-stage cluster sampling or mixed sampling to enhance the generalizability of these findings.

References

Akter, S., Ray, P., & D'Ambra, J. (2013). Continuance of mHealth services at the bottom of the pyramid: the roles of service quality and trust. *Electronic Markets, 23,* 29-47.

Allman-Farinelli, M., Partridge, S., McGeechan, K., Balestracci, K., Hebden, L., Wong, A., Phongsavan, P., DenneyWilson, E., Harris, M., Bauman, A. (2016). A mobile health lifestyle program for prevention of weight gain in young adults (TXT2BFiT): Nine-month outcomes of a randomized controlled trial. *JMIR mHealth and uHealth, 4,* 1-78. doi: 10.2196/mhealth.5678

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50,* 179-211.

Ainscough, K., Kennelly, M., Lindsay, K. L., O'Sullivan, E. J., & McAuliffe, F. M. (2016, July). Impact of an mHealth supported health lifestyle intervention on behavioral stage of change in overweight and obese pregnancy. *Proceedings of the Nutrition Society, 75,* E85. doi:10.1017/S0029665116001002

Bardus, M., van Beurden, S. B., Smith, J. R., & Abraham, C. (2016). A review and content analysis of engagement, functionality, aesthetics, information quality, and change techniques in the most popular commercial apps for weight management. *International Journal of Behavioral Nutrition, 13.* doi: 10.1186/s12966-016-0359-9

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly, 25,* 351–370. URL: http://www.jstor.org/stable/3250921

Burke, L. E., Styn, M. A., Sereika, S. M., Conroy, M. B., Ye, L., Glanz, K., Sevick, M. A., &

Ewing, L. J. (2012). Using mHealth technology to enhance self-monitoring for weight loss: A randomized trial. *American Journal of Preventive Medicine, 43,* 20-26. doi: 10.1016/j.amepre.2012.03.016

Brunstein, A., Brunstein, J., & Mansar, S. L. (2012). Integrating health theories in health and fitness applications for sustained behavior change: Current state of the art. *Creative Education, 3,* 1-5. doi: 10.4236/ce.2012.38b001

Census and Statistics Department (2016). Personal computer and Internet penetration. *Thematic Household Survey Report No. 59*. Hong Kong Special Administrative Region. Retrieved at http://www.statistics.gov.hk/pub/B11302592016XXXXB0100.pdf

Chou, H. K., Lin, I. C., Woung, L. C., & Tsai, M. T. (2012). Engagement in e-Learning opportunities: An empirical study on patient education using expectation confirmation theory. *Journal of Medical System, 26,* 1697-1706. doi:10.1007/s10916-010-9630-9

Chen, S. C., Jong, D., & Lai, M. T. (2014). Assessing the relationship between technology readiness and continuance intention in an e-appointment system: Relationship quality as a mediator. *Journal of Medicine System, 38,* 76-88. doi: 10.1007/s10916-014-0076-3

Chen, S. C., Liu, M. L., & Lin, C. P. (2013). Integrating technology readiness into the expectation–confirmation model: An empirical study of mobile services. *Cyberpsychology, Behavior, and Social Networking, 16,* 604-612. doi:10.1089/cyber.2012.0606

CNNIC. (2017). The 39th China statistical report on Internet development. China Internet Network Information Center. Retrieved from http://www.cnnic.net.cn/hlwfzyj/hlwxzbg/hlwtjbg/201701/P020170123364672657408.p df

Dale, L. P., Whittaker, R., Jiang, Y., Stewart, R., Rolleston, A., & Maddison, R. (2015). Text message and Internet support for coronary heart disease self-management: Results from the text4heart randomized controlled trial. *Journal of Medical Internet Research, 17,* e237. doi: 10.2196/jmir.4944.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical model. *Management Science, 35,* 982-1003.

Edison, S. W., & Geissler, G. L. (2003). Measuring attitudes towards general technology: Antecedents, hypotheses and scale development. *Journal of Targeting, Measurement and Analysis for Marketing, 12*(2), 137-156. doi:10.1057/palgrave.jt.5740104

Festinger, L.A. (1957). *A theory of cognitive dissonance*. Evanston: Row and Peterson.

Fox, S., & Duggan, M. (2012). *Mobile Health 2012.* Washington, DC: Pew Research Center.

Helander, E., Kaipainen, K., Korhonen, I., & Wansink, B. (2014). Factors related to sustained use of a free mobile app for dietary self-monitoring with photography and peer feedback: Retrospective cohort study. *Journal of Medical Internet Research, 16,* e109. doi:10.2196/jmir.3084

Hsiao, W. H., & Chang, T. S. (2014). Understanding consumers' continuance intention towards mobile advertising: a theoretical framework and empirical study. *Behavior & Information Technology, 33,* 730-742. doi: 10.1080/0144929X.2013.789081

Hsu, C. L., & Lin, J. C. C. (2015). What drives purchase intention for paid mobile apps? – An expectation confirmation model with perceived value. *Electronic Commerce Research* *and Applications, 14,* 46-57. doi:10.1016/j.elerap.2014.11.003

Joo, Y. J., Park, S., & Shin, E. K. (2017). Students' expectation, satisfaction, and continuance intention to use digital textbooks. *Computers in Human Behavior, 69,* 83-90. doi:10.1016/j.chb.2016.12.025

Lee, M. C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education, 54,* 506-516. doi: 10.1016/j.compedu.2009.09.002

Lieberman, M. A., & Goldstein, B. A. (2006). Not all negative emotions are equal: The role of emotional expression in online support groups for women with breast cancer. *Psycho-Oncology, 15,* 160-168. doi: 10.1002/pon.932

Lin, J. C., & Hsieh, P. (2006). The role of technology readiness in customers' perception and adoption of self-service technologies. *International Journal of Service Industry Management, 17,* 495-517. doi: 10.1108/09564230610689795

Lin, T. C., Wu, S., Hsu, J. S. C., & Chou, Y. C. (2012). The integration of value-based adoption and expectation–confirmation models: An example of IPTV continuance intention. *Decision Support Systems, 54,* 63-75. doi: 10.1016/j.dss.2012.04.004

Lin, C. P., & Bhattacherjee, A. (2007). Extending technology usage models to interactive hedonic technologies: a theoretical model and empirical test. *Information System Journal, 20,* 163-181. doi: 10.1111/j.1365-2575.2007.00265.x

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research, 2*(3), 173–191. http://dx.doi.org/10.1287/isre.2.3.173

Meuter, M. L., Ostrom, A. L., Bitner, M. J., Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research, 56* (11), 899-906. doi:10.1016/S0148-2963(01)00276-4

Mitchell, J. (1999). *From telehealth to e-health: The unstoppable rise of e-health.* Paper presented at Commonwealth Department of Communications, Information Technology and the Arts (DOCITA), Canberra, Australia.

Norman, C. D., & Skinner, H. A. (2006). eHealth literacy: Essential skills for consumer health in a networked world. *Journal of Medical Internet Research, 8*(2), e9. doi:10.2196/jmir.8.2.e9

Oghuma, A. P., Libaque-Saenz, C. F., Wong, S. F., & Chang, Y. (2016). An expectation-confirmation model of continuance intention to use mobile instant messaging. *Telematics and Informatics, 33,* 34-47. doi: 10.1016/j.tele.2015.05.006

Oliver, R. L. (1980). A cognitive model for the antecedents and consequences of satisfaction. *Journal of Marketing Research, 17,* 460-469.

Oliver, R. L. (1996). *Satisfaction: a behavioral perspective on the consumer*. New York: McGraw Hill.

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2,* 307- 320.

Pennebaker, J. W., & Beall, S. K. (1986). Confronting a traumatic event: Toward an understanding of inhibition and disease. *Journal of Abnormal Psychology, 95*, 274–281.

Quinn, S., Bond, R., & Nugent, C. (2017). Quantifying health literacy and eHealth literacy using existing instruments and browser-based software for tracking online health information seeking behavior. *Computers in Human Behavior, 69*, 256-267. doi: 10.1016/j.chb.2016.12.032

Rogers, E. M. (1995). *Diffusion of Innovations* (4th ed.) New York: Free Press.

Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services: An extension to the expectation-confirmation model. *Industrial Management & Data Systems, 116,* 508-525. doi: 10.1108/IMDS-05-2015-0195

Taylor, S. A., Celuch, K., & Coodwin, S. (2002). Technology Readiness in the e-Insurance Industry: An Exploratory Investigation and Development of an Agent Technology e-Consumption Model. *Journal of Insurance Issues, 25,* 142-165.

van Dijk, M. R., Huijgen, N. A., Willemsen, S. P., Laven, J. S. E., Steegers, E. A. P., Steegers-Theunissen, R. P. M. (2016). Impact of an mhealth platform for pregnancy on nutrition and lifestyle of the reproductive population: A survey. *JMIR mHealth and uHealth, 4,* e53. doi: 10.2196/mhealth.5197

West, J. H., Hall, P. C., Arredondo, V., Berrett, B., Guerra, B., & Farrell, J. (2013). Health behavior theories in diet apps. *Journal of Consumer Health on the Internet, 17*, 10–24. doi:10.1080/15398285.2013.756343

WHO Global Observatory for eHealth. (2011). *New horizons for health through mobile technologies.* Geneva: World Health Organization.

Yan, Y. Y. (2010). Online health information seeking behavior in Hong Kong: An exploratory study. *Journal of Medical Systems, 34,* 147-153. doi:10.1007/s10916-008-9226-9

Yen, H. R. (2005). An attribute-based model of quality satisfaction for Internet self-service technology. *The Service Industries Journal*, *25*(5), 641-659. doi:10.1080=02642060500100833

Zhong, Z., Luo, J., & Zhang, M. (2015). Understanding Antecedents of Continuance Intention in Mobile Travel Booking Service. *International Journal of Business and Management*, *10*, 156-162

Table 1: Frequency in the use of e-health, m-health, and/or wearables to seek health-related information [1]

	e-health		m-health		Wearables	
	n	%	n	%	n	%
Never	196	23.9	419	47.9	790	79.0
Rare	237	28.9	252	28.9	112	11.2
Sometimes	**243**	**29.6**	**124**	**14.2**	**42**	**4.2**
Often	**108**	**13.2**	**56**	**6.4**	**30**	**3.0**
Very often	**36**	**4.4**	**23**	**2.7**	**25**	**2.5**
No response	187		133		7	
n=	387		203		97	

Notes:
[1] Under the post-consumption context, only those who responded ‘sometimes,’ ‘often,’ or ‘very often’ to the question “How often do you use the following health-related information platforms/apps?” were included for subsequent analyses.
N=1,007

Table 2: Factor analysis of e-health/m-health-related information activities via internet platforms/apps

How often do you use internet platforms or mobile apps in the following m-Health-related information activities?	Factors 1	2	3	4	5	6	Mean	s.d.
Health information seeking							2.57	.72
1. To do self-education about a specific disease or medical problems.	.76						2.45	1.09
2. To search information about a specific disease or medical problem.	.68						3.20	.95
3. To search the nearest hospital or clinics.	.67						2.58	1.01
4. To do self-diagnosing.	.54						2.06	.99
Medical services							1.50	.63
5. To pay medical treatment fees.		.78					1.33	.65
6. To buy medicines or health-related products.		.70					1.43	.78
7. To make an appointment with a doctor.		.65					1.75	1.01
Sharing experience							1.49	.77
8. To share opinions on the medical products and services I purchased.			.91				1.58	.91
9. To post comments or stories about my personal health experiences.			.86				1.40	.77
Reminders							1.21	.58
10. To remind myself when to take medicine.				.87			1.23	.74
11. To remind myself of medicine refilling.				.86			1.19	.60
Recording/monitoring							1.69	1.00
12. To record and monitor my sleep quality.					.89		1.50	1.03
13. To record and monitor the amount of exercise.					.73		1.87	1.26
Health tutorial							2.59	.89
14. To seek information on diet, exercise, or fitness.						.77	2.82	1.05
15. To follow the exercise instructions.						.75	2.36	1.07
Eigenvalues	1.99	1.94	1.73	1.71	1.60	1.55		
Variance explained	13.24	12.99	11.54	11.42	10.69	10.33		
Cronbach's alpha	.67	.63	.79	.72	.67	.58		

Scale used: 1=never; 5=very often. Only those who use internet platforms/apps for e-health/m-health-related activities with responses equal 'sometimes,' 'often,' or 'very often' were included for analyses. Excluded were those who responded 'never' or 'rare.' N=387. Missing values were replaced by means.

Table 3: Predicting expectation-confirmation in the use of eHealth-related information and lifestyle improvement

Predictors	Expectation-confirmation				Lifestyle improvement
	Confirmation	PU	Satisfaction	Continuance intention	
Demographics					
Gender (M=1)	-.05	.07	-.07	.03	-.00
Age	-.04	-.01	-.05	-.02	.12**
Education	-.01	-.06	-.07	-.01	-.01
Family income	-.09	-.02	.02	-.07	-.01
Technology readiness					
Optimism	.19***	.18***	.02	.06	.07#
Innovation	.14**	.06	-.04	.08*	.11**
Discomfort	-.13*	.09#	.15**	.05	.00
Insecurity	.02	-.03	.05	.04	-.05
e-Health/m-health activities					
Information-based					
Health information seeking	.09#	.06	-.02	.01	.00
Utility-based					
Medical services	-.10*	.03	-.06	-.05	.08*
Sharing experiences	.04	.12**	.03	.01	-.07*
Reminders	.05	.04	-.02	.02	.05
Recording/monitoring	.07	.04	.01	.04	.11**
Health tutorial	.09#	.07	.11*	.02	.08*
Expectation-confirmation					
Confirmation		.41***	.23***	.33***	.27***
PU			.30***	.21***	.50***
Satisfaction				.27***	.02
Continuance intention					-.06
R^2	.10	.28	.27	.47	.51
Adjusted R^2	.06	.25	.23	.45	.49
F	2.88***	9.45***	8.36***	19.34***	21.53***

Notes: Figures are standardized regression coefficients; N=387. Missing values were replaced by means in the regression analyses.
p <= .1; * p <= .05; ** p <= .01; *** p <= .001

Appendix A: Questionnaire items

Variables	Items
Expectation-confirmation	
Confirmation of expectations (Cronbach's =.88; *M*=2.70, *SD*=.83)	1. My experience with using health-related information platforms/apps is better than what I expected. 2. The service level provides by health-related information platforms/apps is better than what I expected. 3. Overall, most of my expectations from using health-related information platforms/apps are confirmed.
Perceived usefulness (Cronbach's =.78; *M*=2.83, *SD*=.93)	1. I find the use of health-related information platforms/apps effectively make me more knowledgeable. 2. I find the use of health-related information platforms/apps effectively improve my health condition. 3. Using health-related information platforms/apps effectively bring more energy to me.
Satisfaction (Cronbach's =.80; *M*=3.23, *SD*=.48)	My overall experience of health-related information platforms/apps use was: 1. very satisfied 2. very pleased 3. very contented
Continuance intention (Cronbach's =.74; *M*=3.02, *SD*=1.02)	1. I intend to continue using the health-related information or platforms/apps rather than discontinue its use. 2. My intentions are to continue using the health-related information platforms/apps than use any alternative means.
Technology readiness	
Optimism (Cronbach's =.68; *M*=3.88, *SD*=.99)	1. Technology gives me more freedom of mobility. 2. Technology makes me more efficient in my occupation.
Innovation (Cronbach's =.71; *M*=2.71, *SD*=1.01)	1. I often keep up with the latest technological development that I am interested in. 2. I can figure out new high-tech products and services without any help. 3. I am usually among the first in my circle of friends to acquire new technology.
Discomfort (reverse scored) (Cronbach's =.71; *M*=2.89, *SD*=1.07)	1. Technical support lines are not helpful because they do not explain things in plain language. 2. When getting technical support, their behaviors make me feel I am silly. 3. Manual for a high-tech product or service is hard to understand.
Insecurity (reverse scored) (Cronbach's =.78; *M*=3.75, *SD*=1.05)	1. It's not safe to pay online. 2. It's not safe to give the vendor a credit card number over the internet. 3. I worry about that the information I send over the Internet may be seen.
Lifestyle improvement	
Lifestyle improvement (Cronbach's =.75; *M*=2.32, *SD*=.89)	I feel that the use of health-related information platforms/apps: 1. helps my weight control 2. improves my sleep quality 3. motivates me to walk more

Scale used: 1=strongly disagree; 5=strongly agree. N=387