Information Technology & People

The role of trust and health belief in the acceptance of online health services

Jian Mou Donghee Shin Jason Cohen

The Role of Trust and Health Belief in the Acceptance of Online Health Services

Online health information services have the potential to improve consumers' engagement in self-managing their own and their family's health (Harbour and Chowdhury, 2007; Song and Zahedi, 2007; Yi et al., 2013). These services, such as WebMD, Health24, and MedlinePlus, offer consumers a) more convenient and greater access to information for self-managing their health, b) more certainty regarding their health status, and c) development of a social and personal sense of health (Cotton and Gupta, 2004; Harbour and Chowdhury, 2007; Xiao et al., 2014). These services benefit consumers by helping them overcome geographic, temporal, and cost limitations associated with traditional health information channels (Harbour and Chowdhury, 2007; Xiao et al., 2014). They, additionally, enable consumers to understand the different perspectives on various health conditions, and be more informed about and more proactive with their health (Rains, 2007). However, there still exist problems associated with these services that may influence consumer acceptance and usage. For example, one study argues that most health-related information found online is inaccurate or misleading for health-information seekers (Abbasi et al., 2012). The trustworthiness and expertise of information providers has often been questioned (Dutta-Bergman, 2003; Lemire et al., 2008), and the computer-mediated nature of these services may cause added anxiety and concern over the misuse of personal health information (Bansal et al., 2010; Beldad et al., 2010). Consumers' hesitation to use online health information services is therefore not surprising.

If online health information services intend to provide benefits, then understanding variations in their acceptance and use is a research problem that solicits attention. One study suggests that online health-information-seeking is equally important as e-services such as e-shopping, for the young population (aged 18-34) (Fox, 2011), while in the context of this study, in South Africa, the use of online health services is still emerging relative to other e-services (de Lanerolle, 2012). Use of these services may, however, be a special case of e-service acceptance that needs to be understood. This is because its usage involves decision-making processes for health behaviors that are likely to be subject to mechanisms, rather than those associated with typical consumer contexts (Sun et al., 2013) or other task-oriented IS (Kim and Chang, 2007). For example, the quality of an individual's current health, or the risk of becoming ill or exacerbating a condition may be important to predicting the acceptance of these services (Rains, 2007). Consequently, consumer engagement with online health services might best be understood as both a health-related behavior and an e-service usage behavior. Therefore, to better understand variations in the use of such services, it is necessary to consider both theories of health behavior, for example, the Health Belief Model (HBM), as well as e-service usage behavior, for example, the extended valence framework (Kim et al., 2009).

The HBM was developed initially in the 1950s by social psychologists to explain preventive health behavior (Rosenstock, 1974). The model posits that an individual's health behavior depends on the existence of certain beliefs toward a given condition (Chen and Land, 1986). There are four health beliefs in this model that explain why people undertake an action to prevent or control illness conditions, namely perceived susceptibility, perceived severity, perceived benefits, and perceived barriers. However, past HBM studies have mostly focused on explaining traditional health management behaviors, such as smoking cessation, exercise habits, and prevention of skin cancer. Few studies apply the HBM to the context of online health-information-seeking.

The use of online health information services also requires a consumer to be willing to engage with the information provider through the platforms and technologies of an e-service. The use of e-services across contexts as varied as e-shopping (Corbitt et al., 2003; Gefen et al., 2003; Jarvenpaa et al., 2000; Kim et al., 2008; Pavlou, 2003; Teo and Liu, 2007), e-banking (Luo et al., 2010; Yousafzai et al., 2009), online legal services (Cho, 2006), mobile payment services (Chandra et al., 2010; Lu et al., 2011), e-government (Bélanger and Carter, 2008; Shin, 2015), and online health care services (Egea and Gonzalez, 2011; Zahedi and Song, 2008) have been shown to be influenced by consumer trust and risk beliefs, along with their perceptions of e-service usefulness. It is argued that because of the technology-mediated nature of e-services, and the temporal and physical distance between consumers and online providers, both uncertainty and fear of opportunism are inherent in the use of these services. This uncertainty results in increased consumer risk perceptions and creates a greater need for trust (Pavlou, 2003). A recent meta-analysis confirmed trust and risk as being important to consumers' online behaviors across several e-service contexts (Mou and Cohen, 2013). In addition, e-service researchers have shown that consumer perceptions of usefulness or benefits are important for acceptance in both commercial (e.g., Chandra et al., 2010, Gefen et al., 2003; Pavlou, 2003) and non-commercial contexts (e.g., Wu and Chen, 2005). We therefore expect that these concepts of trust, risk, and benefit, which have been combined by Kim et al. (2009) into an extended valence framework, will also be relevant to consumer acceptance in the online health context. While trust, risk, and benefits have been separately considered in the online health information context (e.g., Anderson and Agarwal, 2011; Bansal et al., 2010; Lanseng and Andreassen, 2007; Xiao et al., 2014; Yi et al., 2013), they have not been integrated with the HBM to explain consumer engagement with online health information services.

Therefore, the purpose of this study is to develop and test an integrated HBM and extended valence model of consumer acceptance of online health information services. We test the model using data collected from a sample of undergraduate students using an experimental-scenarios approach, combined with a questionnaire survey.

This paper proceeds as follows: In the next section on the theoretical foundation, the development of the proposed research model and hypotheses are described. Next, the research methodology is outlined. Thereafter, the empirical results are presented, followed by the discussion and implications.

Theoretical Foundation and Hypotheses

The HBM was developed by social psychologists to explain health-related behaviors in social psychology and health science (Janz and Becker, 1984; Rosenstock, 1966; 1974). The basic postulate of this model is that an individual's tendency to adopt health-related behaviors is determined by perceived threats and outcome expectancies. Perceived threats include the perceived susceptibility of the individual to a health-related threat, and perceived severity of the consequences if the threat materializes. Outcome expectancies include the perceived benefits of adopting the health-related behavior relative to the perceived barriers associated with performing the behavior. Self-efficacy to adopt the behavior has also been added to the HBM in more recent studies (Rosenstock et al., 1988). The HBM is outlined in Figure 1. It has become one of the most comprehensive models to understand health-related behaviors and why people undertake (or not) actions to prevent or control illnesses (Carpenter, 2010; Harrison et al., 1992). This study focuses on the information-seeking behavior, and not on subsequent actions that may be undertaken based on the information. The HBM is relevant to explanations of behavioral intention toward health-information-seeking in both online (McKinley and Ruppel, 2014) and off-line contexts (Kim et al., 2012).

The valence framework is developed from the economics and psychology literature to understand consumer behaviors (Kim et al., 2009). It is based on the view that perceived risk and benefit are two fundamental aspects of consumers' purchasing behavior (Peter and Tarpey, 1975). This is because, on one hand, consumers seek to minimize unexpected negative effects, while on the other hand, they intend to maximize the positive effects of purchasing (Kim et al., 2009). In the context of online consumer behaviors, Kim et al. (2009) extended the basic valence framework by adding consumer trust beliefs (see Figure 2). This extended valence framework argues that trust beliefs precede risk perceptions and perceived benefits, and that all three subsequently predict online consumer behaviors.

[Insert Figures 1 and 2 around here]

We are able to consider the integration of these theories because both focus on explaining an individual's behavioral intentions prior to his or her actual behavior. Therefore, we integrated the basic HBM and extended valence models to derive our research model (Figure 3). Our dependent variable, representing consumer acceptance, is the consumer's behavioral intention to use online health information services. Since we identify this behavior as both health and e-service usage behaviors, the model draws on the HBM to identify perceived susceptibility, perceived severity, perceived benefits, and self-efficacy as determinants of intention. Risk perceptions refer to an individual's perceptions of the potential for loss and the seriousness of the outcome, if the loss was to occur (Garbarino and Strahilevitz, 2004). Risk perceptions have been identified as financial, performance, social, physical, psychological, privacy, time, and overall risk in the e-service context (Featherman and Pavlou, 2003). Since these perceptions are considered among the most significant barriers to consumers' online behaviors (Kim et al., 2008), we identify three risks in our study. These are performance, psychological, and time risks. In the healthcare domain, perceived barriers refer to "the assessment of potential negative consequences that may result from taking particular health-related actions" (Brown et al. 1991, p. 51). Barrier perceptions are also predicated on social determinants of health (e.g., race/ethnicity, socio-economic status, and gender) (Payton et al., 2014; Payton, 2015). For instance, in the context of HIV prevention, individuals may face limited access to high-quality healthcare, lack of awareness of HIV, stigma, fear, and discrimination. All such factors can be the barriers that influence individuals' HIV prevention behaviors (Payton et al., 2014). Given the complexity in the term of barrier perceptions in the healthcare domain, we therefore only considered perceived benefit as outcome expectancies. We draw on the extended valence framework to include trust and its effects on both perceived benefits as well as perceived risks. Consistent with the extended valence framework, both perceived benefits and perceived risks are influenced by consumer trust. Given the concerns over the credibility of online information providers (Dutta-Bergman, 2003; Lemire et al., 2008), we identify consumer trust in the online health information provider's ability, benevolence, and integrity as relevant trust beliefs with the potential to influence perceived risks, benefits, and intentions toward these services. Finally, our model reflects that self-efficacy may interact with severity and susceptibility to predict health behaviors (Carpenter, 2010; McKinley and Ruppel, 2014). We outline the variables and describe the development of the model's hypotheses in more detail next.

[Insert Figure 3 around here]

Perceived susceptibility is defined as a feeling of vulnerability to a condition, or a risk perception of contracting a condition (Janz and Becker, 1984). The HBM states that health behavior depends on the degree to which individuals believe they are vulnerable, such that when their vulnerability or perceived susceptibility is high, they are more likely to undertake preventive measures against the health threat. Therefore, increased levels of susceptibility to one or more health threats are likely to increase consumers' intentions to adopt online health services. Past empirical studies on several health behaviors empirically support this link (e.g., Marlow et al., 2009). Hence, we hypothesize:

H1: Perceived susceptibility has a positive effect on consumer behavioral intentions toward online health information services.

Perceived severity relates to the seriousness of the clinical or social consequences of a health condition (Janz and Becker, 1984). The HBM predicts that if people consider the consequences serious, they are more likely to act to avoid negative health outcomes (Rosenstock, 1966). When online health information seekers consider themselves likely to suffer seriously because of not acting to avoid a health-related threat, they are more likely to consider adopting online health services to augment their self-management and health-seeking behaviors (Sun et al., 2013). Previous health behavior studies support this link (e.g., Kim et al., 2012). We therefore hypothesize:

H2: Perceived severity has a positive effect on consumer behavioral intentions toward online health information services.

Risk in the online context is multidimensional (Featherman and Pavlou, 2003; Lim, 2003), with psychological, performance, and time risks likely to be particularly relevant in this context. Psychological risk refers to the possibility that an individual suffers from mental stress or loses self-esteem because of using online health services (Liao et al., 2010) (e.g., use of the service may give the health information seeker an unwanted feeling of anxiety). Performance risk is the loss incurred if the online service does not meet the consumer's expectation (Shin, 2010) (e.g., the consumer may obtain health information that is inaccurate or lacks the expected comprehensiveness). Time risk is the possibility that individuals lose time researching health conditions (Featherman and Pavlou, 2003) (e.g., consumers may waste too much time obtaining the information). The extended valence theory suggests that consumers are motivated to minimize such risks by avoiding related behaviors where risks are considered high. This leads to the following hypothesis:

H3: Perceived risks have a negative effect on consumers' behavioral intentions toward online health information services.

Within the HBM, perceived benefits are defined as the "beliefs regarding the effectiveness of the various actions available in reducing the disease threat" (Janz and Becker 1984, p. 2). The HBM contends that if individuals believe that the perceived benefits from undertaking preventive health actions are greater than the barrier perceptions, then the individual is more likely to adopt the behavior (Kim et al., 2012). This is because they must believe the action to be effective and must associate it with the likelihood of preventing a health outcome. This is necessary to overcome conflicting motives of avoidance and any undesirable consequences that may result from performing the health action (Rosenstock, 1974). Thus, consumers are likely to adopt online health information when they believe that this behavior will either prevent a negative health condition or help them maintain or improve the existing condition. Benefits are also a core belief within the e-service valence framework where they are considered to encourage utility-maximizing consumers to make use of online services (Kim et al., 2009). The use of these services can be more convenient for consumers, empower them, and improve their ability to self-manage their health. Past empirical studies support the effect of perceived benefits of online health service adoption (e.g., Lanseng and Andreassen, 2007). We therefore hypothesize:

H4: Perceived benefits have a positive effect on consumer behavioral intentions toward online health information services.

Self-efficacy is defined as "the conviction that one can successfully execute the behavior required to produce the outcomes" (Bandura, 1997). This is another predictor variable in the HBM that can influence health-related behaviors. Normally, people do not partake in new activities, unless they are confident of their ability in doing so. Specifically, in the online health service context, a consumer's Internet self-efficacy is likely to be important to their online activity. If users are confident in their ability to utilize the Internet, they will be more likely to adopt online health information services and perform related online searching. Past studies have found self-efficacy to exert a strong influence on online health acceptance (Lim et al., 2011; Sun et al., 2013). We therefore hypothesize:

H5a: Internet self-efficacy has a positive effect on consumer behavioral intentions toward online health information services.

The effects of susceptibility and severity on users' health behavior may also be moderated by self-efficacy (Carpenter, 2010; McKinley and Ruppel, 2014). Despite the perceptions of a health threat (i.e., high susceptibility and high severity), individuals who lack self-efficacy to engage with online health providers may view these services as less valuable (McKinley and Ruppel, 2014). Individuals lacking in self-efficacy may feel it beyond their control to search for health information, and thus, perceive the use of online health websites for self-management as less appropriate (Rimal, 2001). Self-efficacy thus enhances the effects of perceived health threats on behavior such that the effects of severity and susceptibility on intentions are likely to be stronger for individuals with higher levels of self-efficacy. Hence, we hypothesize:

H5b: Internet self-efficacy moderates the effect of perceived susceptibility on consumer behavioral intentions toward online health information services.

H5c: Internet self-efficacy moderates the effect of perceived severity on consumer behavioral intentions toward online health information services.

Previous meta-analysis of the HBM revealed that severity is the more proximal predictor variable of behavior for both prevention- and treatment-related actions (Carpenter, 2010). Susceptibility, which is the subjective vulnerability of contracting a condition (Rosenstock, 1974), is unlikely to influence behavior unless the individual judges the condition as serious or severe. Consequently, severity may intervene in the relationship between susceptibility and behavior. Some prior studies have considered this intervening relationship (Milne et al., 2000). Thus:

H6: Perceived severity mediates the effect of perceived susceptibility on consumer behavioral intentions toward online health information services.

Based on Gefen et al. (2003), we define trust as the consumer’s belief in the integrity, benevolence, ability, and predictability of the online health information provider. Trust is important to adoption because uncertainties characterize the use of e-services, which have resulted in consumers’ trust beliefs being considered among the most important psychological states influencing online behaviors (Kim et al., 2008; Pavlou and Gefen, 2002; Shin, 2013). A trusted e-service provider is more likely to be perceived as offering accurate and valuable information that is beneficial to the consumer. Shin (2013) argues that trust reduces uncertainty and encourages the expectation of a satisfactory transaction experience. Trust is, therefore, considered important to consumer intentions to use online health services (Deng et al., 2015; Morgan and Trauth, 2013; Song and Zahedi, 2007; Yi et al., 2013). Therefore, we hypothesize:

H7a: Trust has a positive effect on consumer behavioral intentions toward online health information services.

The extended valence framework suggests that consumers are likely to perceive the potential for benefits only if the online provider is trusted to fulfill its obligations (Kim et al., 2009). If consumers trust an online health service as a reliable and competent provider of health information, they are more likely to believe that the service will improve their effectiveness in managing their health. Past empirical studies in the health context found that trust beliefs positively influence perceived benefits, such as convenience (e.g., Lanseng and Andreassen, 2007). Hence, we hypothesize:

H7b: Trust beliefs have a positive effect on the perceived benefits of online health information.

Trust and risk are arguably closely related. According to the extended valence framework, trust is an antecedent to risk perceptions because it reduces the uncertainties that give rise to risk perceptions. From this perspective, risk mediates the effects of trust on consumer acceptance (Jarvenpaa et al., 2000; Kim et al., 2008, 2009; Nicolaou and McKnight, 2006; Pavlou, 2003). Therefore, we hypothesize:

H7c: Trust beliefs lower the perceived risks associated with using online health information.

Research Methodology

Study design and procedures

To test our hypotheses, we carried out a laboratory-based experimental-scenarios research design in a large national university in South Africa. We selected a university because students constitute an important fraction of online consumers (Kim et al., 2008), and are a primary population using the Internet for health services (Bansal et al., 2010; Yi et al., 2014). Moreover, young people often have difficulties accessing traditional health services, and the Internet can offer them a confidential and convenient way to access relevant information (Gray et al., 2005). Even though college students are believed to be healthy, they still often struggle with maintaining responsible sexual behavior, confronting mental health issues, drug and alcohol abuse, smoking, and poor eating habits (Bansal et al., 2010; Kim et al., 2012; McKinley and Ruppel, 2014). Moreover, a recent study noted that HIV remains a potential threat to the college-going and colored population (Payton and Galloway, 2014). In South Africa, where this study was undertaken, HIV/AIDS represents a significant health issue faced by the student population. One study suggests that 3.4% of students are at risk for HIV prevalence (HEAIDS, 2010). Moreover, other studies in the South African context have recorded that 11.1% of those aged between 18 and 34 have alcohol-abuse disorders, and 4.6% have drug abuse and mental health concerns, such as anxiety and depressive disorders (Herman et al., 2009). There also exist other issues associated with the large international student body, such as requirements for immunizations. Consequently, the student body selected for this study represents a diverse cross-section of the consumer population who confront various health-related issues. Many of these students are also learning to function independently in college without the typical family and support structures that surrounded them in their childhood. The engagement of such consumers with online health information services is thus particularly useful to examine.

In the first phase of our research design, participants were provided an opportunity to gain experience in the use of an online health service by completing several tasks. This was followed by a second phase for completing the survey questionnaire. We invited first-year undergraduate students registered in computer-lab-related courses to participate in the study. There are, in total, around 1,300 first-year students registered for these courses. In the first phase, we introduced the purpose of this study and identified three popular online health service websites to provide a context for the experimental tasks (one leading local health information site and two international sites used in other studies, e.g., Zhang, 2014). The websites were all generic medical, health, and wellness sites accessible to consumers with optional registration. The participants were asked to choose one of the three websites. Self-selection, allowing participants the opportunity to select their own health information website, increased the voluntary nature of the e-service usage process (Zahedi and Song, 2008). The participants were asked to browse their chosen health website for information on a variety of issues in several general health categories that included diet and nutrition, and exercise and fitness, and were asked to complete specific tasks related to their search (see Appendix A). The tasks were adapted and redesigned from those of van Deursen (2012) and Keselman et al. (2008). The use of tasks aims to provide participants with some experience and exposure to their chosen health information website, and to promote variability in the use and attitudes toward using the site for maintaining and self-managing their health. Thus, healthy students interested in generic health maintenance, as well as students with specific health conditions, constitute the study's sample. The scenarios required approximately 25 minutes to complete. In the second phase, the participants were asked to complete an online questionnaire. The questionnaire captured the participants' perceptions on all components of the study's constructs. Demographic questions (e.g., age, gender, and the health-information website experience) were also asked. The questionnaire was pre- and pilot-tested prior to its administration. The relevant ethical clearances were received prior to data collection. To facilitate collection of responses, the questionnaire was distributed via the university's e-learning system. In order to increase the response rate, the participants were given a small token of appreciation for their participation.

Measures

Constructs were operationalized based on previously validated instruments. Behavior intention (BI) was measured using scales developed by Bhattacherjee and Premkumar (2004). Given the online context, self-efficacy (SE) was measured using four items reflecting Internet self-efficacy adopted from Hsu and Chiu (2004). Perceived performance risk (RPE) was measured using the scale by Corbitt et al. (2003), Lee (2009), and Sun (2014). Perceived psychological risk (RPS) was measured using scales developed by Liao et al. (2009). Perceived time risk (RT) was measured by adopting the scales developed by Featherman and Pavlou (2003) and Forsythe et al. (2006). In addition, three items developed by Ng et al. (2009) were used for measuring perceived severity (PSE). Three items developed by Goonawardene et al., (2013) were used to measure perceived susceptibility (PSU). Perceived benefit (PB) was measured by adopting the perceived usefulness scale developed by Bhattacherjee and Premkumar (2004). The three dimensions of trust (benevolence, ability, and integrity) were measured using scales developed by Hwang and Lee (2012) and Thatcher et al. (2012). Demographic questions collected data on age and gender. Further, the respondents were asked if they had prior experience in using online health services.

All items were measured using a seven-point Likert-scale with anchors from "strongly disagree" to "strongly agree." Measurement items for each construct are presented in Appendix B.

Results

Participants

In total, 761 respondents completed our online scenarios and questionnaire. However, 58 responses were subsequently eliminated, as they either were missing several data values or exhibited unclear response patterns. Following the approach of Ragu-Nathan et al. (2008), the remaining sample (N = 703) was randomly split into two sets. Set 1 (350 cases) was used for scale-refinement through principal components analysis (PCA). Set 2 (353 cases) was used as a holdout sample for partial least squares (PLS) analysis of the measurement model and structural model. Since the participants were allowed to choose from three online health information providers for undertaking the tasks and gaining familiarity with the online health service context, we performed an analysis of variance (ANOVA) to determine if the trust, perceived risks, self-efficacy, health beliefs, and intention scores were independent of the choice of provider. The results indicated that there were no significant differences among the items measuring trust, perceived risks, self-efficacy, health belief variables, or intention variables.

Table 1 reports the demographic profile of the final 703 responses. The results show that 46.5% of the respondents were male, and 53.5% female. Among the total respondents, 52.1% have online health-information-seeking experience. Most of the participants chose website 1 and website 2 for the scenario tasks, and only a few chose website 3. An ANOVA showed that there were no significant differences across the three website choices. The largest age group comprised those aged 18 to 19 (85.1%). Moreover, most participants had a smartphone (84.6%), and 76.2% had over four years' computer usage experience.

[Insert Table 1 around here]

Common method bias

We checked for common method bias by performing Harman's one factor test (Podsakoff and Organ, 1986). According to this test, common method variance is present if one factor accounts for majority of the covariance in the dependent and independent variables. An exploratory factor analysis of all the scale items revealed factors explaining 68.3% (N = 703) of the variance in our study's constructs, with the first factor explaining 24.8%, and the last explaining 3.5%, of the total variance. These results suggest that no single factor explained a majority of the variance, thus supporting the idea that common method bias was not a threat to this study.

We collected an additional 41 responses from students not registered in our surveyed classes and who were present at different times of the day in other computer laboratories across the campus. We compared their responses to those from our sample (N = 703). No significant differences were found in the responses, except for two items, which is most likely due to chance, given the number of items included in the instrument. Thus, it can be said that the timing of our surveys, or the laboratory conditions or locations influenced our results.

Scale refinement

An initial PCA was undertaken to confirm the unidimensionality of the measures and to eliminate any inappropriate items (N = 350). We removed SE3 at this stage. Thereafter, we carried out a separate PCA on the holdout (N = 353) and the total sample (N = 703) to determine if the same factor structures are reproduced. The results indicated that both the holdout and total samples produced identical factor structures with SE3 eliminated and all items loaded on their expected theoretical constructs.

Measurement model assessment

We further assessed the reliability and validity for each measure using the Smart-PLS software package (version 2.0 M3) (Ringle et al., 2005). We tested two measurement and two structural models, one of each using the holdout sample (dataset 2: N=353), and one of each using the entire dataset (N=703). We tested the measurement model with respect to internal consistency and discriminant validity. Table 2 reports the item loadings, average variance extracted (AVE), composite reliability (CR), and alpha value for the measures of the three dimensions of perceived risks—performance risk (REP), time risk (RT), and psychological risk (RPS), as well as the three dimensions of trust—benevolence (TRB), ability (TRA), and integrity (TRI). For cross-loading, reliability, and validity of behavioral intention, self-efficacy, perceived susceptibility, and severity are reported in Appendix C. All item loadings are above .70. Moreover, none of the items exhibited high cross-loadings on factors not intended to be measured. Our AVE results ranged from .702 to .946 (full dataset), and from .704 to .942 (holdout sample), which are both above the recommended threshold value of .50. Moreover, for scale reliability, all the CR values are above .875, and the alpha values above .734, which are also above the acceptable values. Thus, this confirms the convergent validity. We verified the discriminant validity of the constructs by checking the square root of the AVE. As shown in Table 3, the square root of the AVE of each construct is larger than the inter-construct correlations, and thus, discriminant validity is confirmed.

[Insert Table 2 around here]

[Insert Table 3 around here]

Structural model assessment and hypothesis testing

After validating the measurement model, the hypotheses were tested by assessing the structural model in PLS, which is a variance-based approach to model causal relationships among variables (Urbach and Ahlemann, 2010). PLS provides a good approximation of alternative covariance-based approaches to structural equation modeling in terms of final estimates (Gefen et al., 2011; Hair et al., 2011; Sun et al., 2013). The Bootstrap method (1,000 re-samples) was used to determine the significance of the paths within the structural model. We controlled for the effects of age, gender, online heath-information-service experience, computer experience, and smartphone ownership. This is because a previous study suggests that demographic characteristics may influence online health-service-adoption behavior (Ybarra and Suman, 2008). However, in our study, none of the control variables had a significant effect on behavior intention. Our model explains 47.6% of the variance in intentions to use the online health information services. We also tested our model by using the full dataset (N = 703), which indicated that the R^2 value for consumer intention in online health information is .44, implying that the model explains 44% of the variance. The standardized path coefficients (β) results (N = 353) of model testing are depicted in Figure 4.

As seen in Figure 4, perceived susceptibility had a significant positive effect on intention (β = .160, t = 3.773), and thus, H1 was supported. Perceived severity had a significant positive effect on intention (β = .173, t = 3.745), supporting H2. Perceived risk as a higher-order factor had a significant negative effect on intention (β = -.163, t = 3.802), and thus, H3 was supported. Perceived benefit had a significant positive effect on intention (β = .106, t = 2.207), and hence, H4 was supported. However, self-efficacy had no significant effect on consumer intention (β

= .046, t = 1.076). Therefore, H5a was rejected. The moderation effect indicates that self-efficacy moderated the effects of perceived severity on behavior intention (β = -.121, t = 2.731), although the perceived susceptibility's effect was not moderated by self-efficacy (β = -.004, t = .065). Thereby, H5c was supported, and H5b was rejected. Perceived susceptibility had a significant positive effect on perceived severity (β = .343, t = 6.950), thus supporting H6. Trust as a higher-order factor, had a significant positive effect on intention (β = .424, t = 9.442) and on perceived benefits (β = .365, t = 6.648), as well as a significant negative effect on perceived barriers (β=-.374, t = 8.249). Hence, H7a, H7b, and H7c were supported. Table 4 summarizes the results of this study.

[Insert Figure 4 around here]

[Insert Table 4 around here]

Discussion

This study aimed to examine the factors influencing individuals' use of online health information services. For this, we integrated the HBM and extended valence framework, and empirically tested our research model. Data was collected in a laboratory setting from a sample of university students. Our study resulted in several important and heuristic findings. Interestingly, we found that perceived severity mediates the effect of perceived susceptibility on consumer behavioral intentions toward online health information services. We confirmed that severity intervenes in the relationship between susceptibility and behavior. This relationship has not been adequately discussed in prior literature, and needs further exploration.

First, both perceived susceptibility and perceived severity had a significant positive impact on consumer acceptance of online health information services. The results show that the use of these services is a health-related behavior, and that consistent with the HBM, health threats are important to this behavior.

Second, outcome expectancies (perceived benefits) do have a significant impact on behavioral intention. We found that perceived benefit positively influences intention. This finding is consistent with the theories of HBM. The results suggest that online health information providers should maximize perceived benefits to promote positive intentions toward using online health information. This implies that consumers value information that will help improve their performance in managing their health. Importantly, online health information providers should understand that risk has a multidimensional nature and that performance, psychological, and time losses are important risks for consumers.

Third, it is worth noting that self-efficacy had a non-significant impact on consumer intentions. This is not consistent with the HBM, although a non-significant relationship between self-efficacy and intention has been found in other health behavioral studies (e.g., Wong and Tang, 2005). This can be explained by the possibility that younger online consumers (who constituted our study sample) may possess greater Internet self-efficacy (which was examined in our model), thereby making this factor less relevant to their acceptance of online health services than in the case of a broader consumer sample (McKinley and Ruppel, 2014).

Fourth, self-efficacy was found to negatively moderate the effect of perceived severity on behavioral intentions toward online health information services. Thus, when individuals have low self-efficacy, perceived severity is more important to their behavioral intentions. Therefore, for individuals with lower self-efficacy, it is only when confronted by serious clinical or social consequences of a health condition that they are able to overcome lower self-efficacy to engage in the use of online services. This is, however, contradictory to our expectation that individuals with lower self-efficacy may perceive less value in the use of online health sites to act against health threats. We did not, however, find self-efficacy to moderate the relationship between perceived susceptibility and behavioral intention. This result is inconsistent with Carpenter's (2010) suggestion. Perceived susceptibility, however, has a significant direct effect on perceived barriers. Moreover, participants who consider themselves more vulnerable to a health threat are more likely to be concerned with the risks associated with using the online service. Severity was also shown to partially intervene in the effects of susceptibility. The seriousness of the health condition, not just the vulnerability to it, is important to behavior.

Fifth, we found that trust had the strongest direct impact on behavioral intention. This finding supports the view that trust is important to consumer acceptance of online health services. Thus, the use of these services is driven by typical e-service concerns for trust in the ability, benevolence, and integrity of the online provider. This is a particularly useful finding for service providers. In addition, consumer trust had a strongly significant negative effect on perceived risks. This supports the arguments that trust effectively lowers risks to consumer acceptance of e-services (e.g., Gefen et al., 2003; Pavlou, 2003). Finally, perceived benefit was influenced by trust beliefs. This result indicates that consumers believe they will gain benefits only from a trusted health information provider. The findings are consistent with the extended valence framework.

Implications and Conclusion

Theoretical implications

From a theoretical perspective, our study makes the following contributions. First, this study attempted to extend the valence framework to the non-commercial service context. More specifically, we empirically validated this theoretical framework into the online health-information-service area. Previous applications have focused on e-commerce or mobile commerce (e.g., Kim et al., 2009; Lin et al., 2014; Lu et al., 2011). So far, there are no studies adopting the extended valence framework to study online health behaviors.

Second, unlike several previous studies of the HBM that examine general health behaviors (e.g., Kim et al., 2012; Marlow et al., 2009), we have shown its additional relevance to the study of online health information seeking and have extended recent work (McKinley and Ruppel, 2014). This can broaden the domain of the HBM as the finding link of HBM to emerging health information sites.

Our results indicate that health beliefs and the valence framework are two fundamental aspects that health information seekers consider when making decisions about online health services. To the best of our knowledge, no other study has integrated the HBM and extended valence framework to study online heath behaviors.

Third, the results of this study highlight the role of trust beliefs and risk perceptions in the context of consumer acceptance of online health information services. More specifically, we identified the multifaceted risks to include performance, psychological, and time risks. Trust beliefs include the online service provider’s ability, benevolence, and integrity. Moreover, we show that trust is not only salient in commercial e-service contexts, but also extends to the non-commercial online health services context. Our findings on trust and risk perceptions can be reliably modeled as a higher-order construct. This can help future researchers to comprehensively capture these constructs in the e-service context.

Practical implications

First, our study found that trust has the strongest direct effect on behavioral intentions. The importance of the three dimensions of trust in this study, namely online health services providers' ability, benevolence, and integrity, can help practitioners better understand the development of trust. Practitioners need to ensure that they increase provider-based trust by building their reputation as a reliable, competent provider of health information and one that acts in the best interest of consumers, unlike, for example, pharmaceutical companies or commercial advertisers. As this study confirmed the role of trust for individuals seeking health information online, the e-health industry may strive to understand the trust-building mechanism. Health information websites can incorporate third-party trust seal programs to increase consumer trust beliefs, and promote their reputation via online testimonials.

Second, the salient and negative effect of perceived risks on intentions implies that risks play an important role in dampening consumers' online health-information acceptance behavior. Through modeling, perceived risks were identified as performance, psychological, and time risks that negatively affect online health information acceptance. This suggests that when online health service providers promote their information to encourage the potential online health information seekers, they should use countermeasures against those risks. For example, an online service provider may reduce performance risk by providing evidence of sources used to compile the information; mitigate time loss by providing a friendly interface, good search navigation and a clear index of categories; and break the psychological anxieties associated with site use by providing simple and actionable information.

Third, perceived benefits, perceived susceptibility, and perceived severity are other important factors influencing consumer behavior. Since perceived benefit is considered an important determinant for individuals seeking health information online, practitioners should draw on the needs of the information seekers by providing useful health services to them, enhancing effectiveness, and improving performance. In this way, they could gain more market share. Individuals are more likely to seek health information when they perceive their general health as poor and when they have a need for access to health information. This finding can help service providers understand the profiles of consumers who may browse their sites and how perceived health threats as well as the need for improved self-management are important to their motivation. Health information sites should empower self-management in a manner that allows for better decision-making based on differing levels of susceptibility and severity, such as through advanced search options.

Limitations and future research

While the findings are notable, the results of this study should be interpreted with caution, as it has some limitations. First, the sample was drawn from a university population, and this could negatively affect the generalization of the conclusions to broader consumer populations. Future research could conduct a similar study using other samples, such as adults with chronic diseases. Second, some of the tasks may not be applicable to all consumers and may have created bias in their perceptions (Lanseng and Andreassen, 2007). Third, our data was also cross-sectional, and therefore, causal inferences could only be made with reference to theory. Future studies could adopt longitudinal designs and consider the temporal changes in the extended valence framework as well as the health belief behavior toward online health services. Since this study has confirmed trust as being multidimensional and highly important to acceptance, future research could determine the specific antecedents of trust in digital health innovations, and could consider other variables potentially unique to the healthcare context, such as emotion (Anderson and Agarwal, 2011). Moreover, future research could conduct a longitudinal study to consider whether trust and health beliefs change over time. For example, some researchers have argued that earlier beliefs may influence later beliefs in consumer acceptance of new technology (e.g., Bhattacherjee and Premkumar, 2004; Hsu et al., 2006; Venkatesh et al., 2011).

Conclusion

This study develops a research model to understand consumer acceptance of online health information services by integrating the HBM and extended valence framework. We used a laboratory-based experimental-scenarios research design to collect data from a sample of 703 university students in South Africa. To test our hypotheses, trust and perceived risk were modeled as higher-order constructs. Our multidimensional trust construct was found to exert the strongest effect on consumer acceptance. Perceived risks were also found to have a direct significant negative effect on consumer acceptance. Furthermore, we confirmed that health belief variables, such as perceived susceptibility and severity, were important to consumer acceptance of online health information services and that perceived susceptibility had a significant positive effect on perceived severity. Self-efficacy had non-significant effects on intentions; however, it was found to moderate the effect of perceived severity on consumer behavioral intentions. The model explains 47.6% of the variance in intentions to use the online health information services, which is fairly high. Compared to previous studies (e.g., R^2=.29, Shin, 2013), this variance is considered noteworthy and can be a significant theoretical and practical advancement. The results have helped us identify the relative salience of the HBM and extended valence framework in consumer acceptance of online health information services, which has important practical implications.

References

Abbasi, A., Zahedi, F. M. and Kaza, S. (2012), "Detecting fake medical websites using recursive trust labeling", *ACM Transactions on Information Systems*, Vol. 30 No. 4, pp. 1-36.

Anderson, C. L. and Agarwal, R. (2011), "The digitization of healthcare: Boundary risks, emotion, and consumer willingness to disclose personal health information", *Information Systems Research*, Vol. 22 No. 3, pp. 469-490.

Bandura, A. (1997), *Self-efficacy: The Exercise of Control*. New York: W. H. Freeman.

Bansal, G., Zahedi, F. M. and Gefen, D. (2010), "The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online", *Decision Support Systems*, Vol. 49, pp. 138-150.

Beldad, A., de Jong, M. and Steehouder, M. (2010), "How shall I trust the faceless and the intangible? A literature review on the antecedents of online trust", *Computer in Human Behavior*, Vol. 26, pp. 857-869.

Bélanger, F. and Carter, L. (2008), "Trust and risk in E-government adoption", *Journal of Strategic Information Systems*, 17, pp. 165-176.

Bhattacherjee, A. and Premkumar, G. (2004), "Understanding changes in belief and attitude toward information technology usage: A theoretical model and longitudinal test", *MIS Quarterly*, Vol. 28 No. 2, pp. 229-254.

Brown, L. K., DiClemente, R. J. and Reynolds, L. A. (1991). "HIV prevention for adolescents: Utility of the Health Belief Model", AIDS Education & Prevention, Vol. 3, pp. 50-59.

Carpenter, C. J. (2010), "A meta-analysis of the effectiveness of health belief model variables in predicting behavior", *Health Communication*, Vol. 25, pp. 661-669.

Chandra, S., Srivastava, S. C. and Theng Y. L. (2010), "Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis", *Communications of the Association for Information Systems*, Vol. 27, pp. 561-588.

Chen, M. S. and Land, K. C. (1986), "Testing the health belief model: LISREL analysis of alternative models of causal relationships between health beliefs and preventive dental behavior", *Social Psychology Quarterly*, Vol. 49 No. 1, pp. 45-60.

Cho, V. (2006), "A study of the roles of trusts and risks in information-oriented online legal services using an integrated model", *Information and Management*, Vol. 43, pp. 502-520.

Corbitt, B. J., Kracher, B. and Yi, H. (2003), "Trust and e-commerce: A study of consumer perceptions", *Electronic Commerce Research and Applications*, Vol. 2 No. 3, pp. 203-215.

Cotton, S. R. and Gupta, S. S. (2004), "Characteristics of online and offline health information seekers and factors that discriminate between them", *Social Science and Medicine*, Vol. 59, pp. 1795-1806.

de Lanerolle, A. (2012), *The new wave report: Who connects to the Internet, how they connect and what they do when they connect*. Wits Journalism, University of Witwatersrand, Johannesburg, South Africa. Retrieved from http://www.worldinternetproject.net/_files/_Published/_oldis/413_wip_south_african_2012.pdf

Deng, Z., Liu, S. and Hinz, O. (2015). "The health information seeking and usage behavior intention of Chinese consumers through mobile phones", *Information Technology & People*, Vol. 28 No. 2, pp. 405-423.

Dutta-Bergman, M. (2003), "Trusted online sources of health information: Differences in demographics, health beliefs, and health-information orientation", *Journal of Medical Internet Research*, Vol. 5 No. 3, e21.

Egea, J. M. O. and Gonzalez, M. V. R. (2011), "Explaining physicians' acceptance of EHCR systems: An extension of TAM with trust and risk factors", *Computers in Human Behavior*, Vol. 27, pp. 319-332.

Featherman, M. S. and Pavlou, P. A. (2003), "Predicting E-services adoption: A perceived risk facets perspective", *International Journal of Human-Computer Studies*, Vol. 59, pp. 451-474.

Forsythe, S., Liu, C., Shannon, D. and Gardner, C. (2006), "Development of a scale to measure the perceived benefits and risks of online shopping", *Journal of Interactive Marketing*, Vol. 20 No. 2, pp. 55-75.

Fox, S. (2011), *Health topics*. Pew Internet and American Life Project. Retrieved from http://pewinternet.org/Reports/2011/HealthTopics.aspx.

Garbarino, E. and Strahilevitz, M. (2004). "Gender differences in the perceived risk of buying online and the effects of receiving a site recommendation," *Journal of Business Research,* Vol. 57, pp. 768-775.

Gefen, D., Karahanna, E. and Straub, D. W. (2003), "Trust and TAM in online shopping: An integrated model", *MIS Quarterly*, Vol. 27 No. 1, pp. 51-90.

Gefen, D., Rigdon, E. E. and Straub, D. (2011), "An update and extension to SEM guidelines for administrative and social science research", *MIS Quarterly*, Vol. 35 No. 2, pp. iii-xiv.

Goonawardene, N., Jiang, J., Tan, S. S. L. and Jiang, Z. (2013), "Online health information seeking and adolescents' intention towards health self-management", *PACIS Proceedings.* Paper 174.

Gray, N. J., Klein, J. D., Noyce, P. R., Sesselberg, T. S. and Cantrill, J. A. (2005), "Health information-seeking behaviour in adolescence: The place of the Internet", *Social Science and Medicine*, Vol. 60, pp. 1467-1478.

Hair, J. F., Ringle, C. M. and Sarstedt, M. (2011), "PLS-SEM: Indeed a silver bullet", *The Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152.

Harbour, J. and Chowdhury, G. G. (2007), "Use and outcome of online health information services: A study among Scottish population", *Journal of Documentation*, Vol. 63 No. 2, pp. 229-242.

Harrison, J. A., Mullen, P. D. and Green, L. (1992), "A meta-analysis of studies of the health belief model with adults", *Health Education Research*, Vol. 7 No. 1, pp. 107-116.

HEAIDS (2010), *HIV Prevalence and Related Factors-Higher Education Sector Study, South Africa, 2008-2009*. Pretoria: Higher Education South Africa.

Herman, A. A., Stein, D. J., Seedat, S., Heeringa, S. G., Moomal, H. and Williams, D. R. (2009), "The South African stress and health (SASH) study: 12-month and lifetime prevalence of common mental disorders", *South African Medical Journal*, Vol. 99 No. 5, pp. 33-35.

Hsu, M. H. and Chiu, C. M. (2004), "Internet self-efficacy and electronic service acceptance", *Decision Support Systems*, Vol. 38, pp. 369-381.

Hsu, M. H., Yen, C. H., Chiu, C. M. and Chang, C. M. (2006), "A longitudinal investigation of continued online shopping behavior: An extension of the theory of planned behavior", *International Journal of Human-Computer Studies*, Vol. 64 No. 9, pp. 889-904.

Hwang, Y. and Lee, K. C. (2012), "Investigating the moderating role of uncertainty avoidance cultural value on multidimensional online trust", *Information and Management*, Vol. 49, pp. 171-176.

Janz, N. K. and Becker, M. H. (1984), "The health belief model: A decade later", *Health Education Quarterly*, Vol. 11, pp. 1-47.

Jarvenpaa, S. L., Tracinsky, N. and Vitale, M. (2000), "Consumer trust in an Internet store", *Information Technology and Management*, Vol. 1 No. 1, pp. 45-71.

Keselman, A., Browne, A. C. and Kaufman, D. (2008), "Consumer health information seeking as hypothesis testing", *Journal of the American Medical Informatics Association*, Vol. 15 No. 4, pp. 484-495.

Kim, H. S., Ahn, J. and No, J. K. (2012), "Applying the health belief model to college student's health behavior", *Nutrition Research and Practice*, Vol. 6 No. 6, pp. 551-558.

Kim, D. and Chang, H. (2007), "Key functional characteristics in designing and operating health information websites for user satisfaction: An application of the extended technology acceptance model", *International Journal of Medical Informatics*, Vol. 76, pp. 790-800.

Kim, D. J., Ferrin, D. L. and Rao, H. R. (2008), "A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents", *Decision Support Systems*, Vol. 44 No. 2, pp. 544-564.

Kim, D. J., Ferrin, D. L. and Rao, H. R. (2009), "Trust and satisfaction, two stepping stones for successful E-commerce relationships: A longitudinal exploration", *Information Systems Research*, Vol. 20 No. 2, pp. 237-257.

Lanseng, E. J. and Andreassen, T. W. (2007), "Electronic healthcare: A study of people's readiness and attitude toward performing self-diagnosis", *International Journal of Service Industry Management*, Vol. 18 No. 4, pp. 394-417.

Lee, M. C. (2009), "Factors influencing the adoption of Internet banking: An integration of TAM and TPB with perceived risk and perceived benefit", *Electronic Commerce Research and Applications*, Vol. 8, pp. 130-141.

Lemire, M., Paré, G., Sicotte, C. and Harvey, C. (2008), "Determinants of Internet use as a preferred source of information on personal health", *International Journal of Medical Informatics*, Vol. 77, pp. 723-734.

Liao, C., Lin, H. N. and Liu Y. P. (2010), "Predicting the use of pirated software: A contingency model integrating perceived risk with the theory of planned behavior", *Journal of Business Ethics*, Vol. 91, pp. 237-252.

Lim, N. (2003), "Consumers' perceived risk: Sources versus consequences", *Electronic Commerce Research and Applications*, Vol. 2, pp. 216-228.

Lim, S., Xue, L., Yen, C. C., Chang, L., Chan, H. C., Tai, B. C., Duh, H. B. L. and Choolani, M. (2011), "A study on Singaporean women's acceptance of using mobile phones to seek health information", *International Journal of Medical Informatics*, Vol. 80, pp. e189-e202.

Lin, J., Wang, B., Wang, N. and Lu, Y. (2014), "Understanding the evolution of consumer trust in mobile commerce: A longitudinal study", *Information Technology and Management*, Vol. 15 No. 1, pp. 37-49.

Lu, Y., Yang, S., Chau, P. Y. K. and Cao, Y. (2011), "Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective", *Information and Management*, Vol. 48, pp. 393-403.

Luo, X., Li, H., Zhang, J. and Shim, J. P. (2010), "Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services", *Decision Support Systems*, Vol. 49, pp. 222-234.

Marlow, L. A. V., Waller, J., Evans, R. E. C. and Wardle, J. (2009), "Predictors of interest in HPV vaccination: A study of British adolescents", *Vaccine*, Vol. 27, pp. 2483-2488.

McKinley, C. J. and Ruppel, E. K. (2014), "Exploring how perceived threat and self-efficacy contribute to college students' use and perceptions of online mental health resources", *Computer in Human Behavior*, Vol. 34, pp. 101-109.

Milne, S., Sheeran, P. and Orbell, S. (2000), "Prediction and intervention in health-related behavior: A meta-analytic review of protection motivation theory", *Journal of Applied Social Psychology*, Vol. 30 No. 1, pp. 106-143.

Morgan, A. J. and Trauth, E. M. (2013), "Socio-economic influences on health information searching in the USA: the case of diabetes", *Information Technology & People*, Vol. 26 No. 4, pp. 324-346.

Mou, J. and Cohen, J. F. (2013), "*Trust and risk in consumer acceptance of E-services: A meta-analysis and a test of competing models*", In Proceedings of the Thirty-Fourth International Conference on Information Systems.

Nicolaou A. I. and McKnight D. H. (2006), "Perceived information quality in data exchanges: Effects on risk, trust, and intention to use", *Information Systems Research*, Vol. 17 No. 4, pp. 332-351.

Ng, B., Kankanhalli, A. and Xu, Y. (2009), "Studying users' computer security behavior: A health belief perspective", *Decision Support Systems*, Vol. 46, pp. 815-825.

Pavlou, P. A. (2003), "Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model", *International Journal of Electronic Commerce*, Vol. 7 No. 3, pp. 101-134.

Pavlou, P. A. and Gefen, D. (2002), "*Building effective online marketplaces with institution-based trust*", In Proceedings of the Twenty-Third International Conference on Information Systems.

Payton, F. C. (2015), "Cultures of participation—for students, by students", *Information Systems Journal*, doi: 10.1111/isj.12086.

Payton, F. C. and Galloway, K. (2014). " Here comes the # Engagement: A serious health initiative made trendy", *XRDS*, Vol. 21 No. 2, pp. 28-31.

Payton, F. C., Kvasny, L. and Kiwanuka-Tondo, J. (2014), "Online HIV prevention information: How black female college students are seeking and perceiving", *Internet Research*, Vol. 24 No. 4, pp. 520-543.

Peter, P. J. and Tarpey, L. X. (1975), "A comparative analysis of three consumer decision strategies", *Journal of Consumer Research*, Vol. 2 No. 1, pp. 29-37.

Podaskoff, P. M. and Organ, D. W. (1986), "Self-reports in organizational research: Problems and Prospects", *Journal of Management*, Vol. 12, pp. 531-544.

Ragu-Nathan, T. S., Tarafdar, M. and Ragu-Nathan, B. S. (2008), "The consequences of technostress for end users in organizations: Conceptual development and empirical validation", *Information Systems Research*, Vol. 19 No. 4, pp. 417-433.

Rains, S. A. (2007), "Perceptions of traditional information sources and use of the World Wide Web to seek health Information: Findings from the Health Information national trends survey", *Journal of Health Communication*, Vol. 12, pp. 667-680.

Rimal, R. N. (2001), "Perceived risk and self-efficacy as motivators: Understanding individuals' long-term use of health information", *Journal of Communication*, Vol. 51 No. 4, pp. 633-654.

Ringle, C. M., Wende, S. and Will, A. (2005), SmartPLS (Release 2.0), University of Hamburg, Hamburg, Germany. Retrieved from http://www.smartpls.de

Rosenstock, I. M. (1966), "Why people use health services", *Millbank Memorial Fund Quarterly*, Vol. 44, pp. 94-124.

Rosenstock, I. M. (1974), "Historical origins of the health belief model", *Health Education and Behavior*, Vol. 2 No. 4, pp. 328-355.

Rosenstock, I. M., Strecher, V. J. and Becker, M. H. (1988), "Social learning theory and the health belief model", *Health Education Quarterly*, Vol. 15 No. 2, pp. 175-183.

Shin, D. (2015), "Beyond user experience of cloud service: Implication for value sensitive", *Telematics and Informatics*, Vol. 32 No. 1, pp. 33-44.

Shin, D. (2013), "User experience in social commerce: In friends we trust", *Behavior and Information Technology*, Vol. 32 No. 1, pp. 52-67.

Shin, D. (2010), "Ubiquitous computing acceptance model: End user concern about security, privacy and risk", *International Journal of Mobile Communications*, Vol. 8 No. 2, pp. 169-186.

Song, J. and Zahedi, F. M. (2007), "Trust in health informediaries", *Decision Support Systems*, Vol. 43, pp. 390-407.

Sun, J. (2014), "How risky are services? An empirical investigation on the antecedents and consequences of perceived risk for hotel service", *International Journal of Hospitality Management*, Vol. 37, pp. 171-179.

Sun, Y., Wang, N., Guo, X. and Peng Z. (2013), "Understanding the acceptance of mobile health service: A comparison and integration of alternative models", *Journal of Electronic Commerce Research*, Vol. 14 No. 2, pp. 183-200.

Teo, T. S. H. and Liu, J. (2007), "Consumer trust in E-commerce in the United States, Singapore and China", *The International Journal of Management Science*, Vol. 35, pp. 22-38.

Thatcher, J. B., Carter, M., Li, X. and Rong, G. (2013), "A classification and investigation of trustees in B-to-C E-commerce: General vs. specific trust", *Communications of the Association for Information Systems*, Vol. 32, pp. 107-134.

Urbach, N. and Ahlemann, F. (2010), "Structural equation modeling in information systems research using partial least squares", *Journal of Information Technology Theory and Application*, Vol. 11 No. 2, pp. 5-40.

van Deursen, A. J. A. M. (2012), "Internet skill-related problems in accessing online health information", *International Journal of Medical Informatics*, Vol. 81, pp. 61-72.

Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., Hu, P. J. H. H. and Brown, S. A. (2011), "Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context", *Information Systems Journal*, Vol. 21, pp. 527-555.

Wong, C. Y. and Tang, C. S. K. (2005), "Practice of habitual and volitional health behaviors to prevent severe acute respiratory syndrome among Chinese adolescents in Hong Kong", *Journal of Adolescent Health*, Vol. 36, pp. 193-200.

Wu, I. L. and Chen, J. L. (2005), "An extension of trust and TAM model with TPB in the initial adoption of on-line tax: An empirical study", *International Journal of Human-Computer Studies*, Vol. 62, pp. 784-808.

Xiao, N., Sharman, R., Rao, H. R. and Upadhyaya, S. (2014), "Factors influencing online health information search: An empirical analysis of a national cancer-related survey", *Decision Support Systems*, Vol. 57, pp. 417-427.

Ybarra, M. and Suman, M. (2008), "Reasons, assessments and actions taken: Sex and age differences in uses of Internet health information", *Health Education Research*, Vol. 23 No. 3, pp. 512-521.

Yi, M.Y., Yoon, J. J., Davis, J. M. and Lee, T. (2013), "Untangling the antecedents of initial trust in web-based health information: The roles of argument quality, source expertise, and user perceptions of information quality and risk", *Decision Support Systems*, Vol. 55, pp. 284-295.

Yousafzai, S.Y., Pallister, J. G. and Foxall, G. R. (2009), "Multi-dimensional role of trust in Internet banking adoption", *The Service Industries Journal*, Vol. 29 No. 5, pp. 591-605.

Zahedi, F. M. and Song, J. (2008), "Dynamic of trust revision: Using health infomediaries", *Journal of Management Information Systems*, Vol. 24 No. 4, pp. 225-248.

Zhang, Y. (2014), "Searching for specific health-related information in MedlinePlus: Behavioral patterns and user experience", *Journal of the Association for Information Science and Technology*, Vol. 65 No. 1, pp. 53-68.

Appendix A

Task Sheet

Please visit one of the following websites:

Website 1: [xxx]; Website 2: [xxx]; Website 3: [xxx]

1. Which website did you visit?

Please complete the following tasks using your chosen website.

2. Identify a health-related topic of your interest. Then, using your chosen website's search feature, search for information on this topic. How relevant did you find the articles?

A. Not at all relevant. B. Somewhat relevant. C. Relevant. D. Very relevant.

3. Read one of the articles, and answer the following questions:

What is its title?

When was it written?

4. What information is required to register or sign up on your chosen website?

5. Does this website contain information on secondhand smoke?

A. Yes B. No

6. Imagine that you are visiting an elderly relative who lives alone in another part of the country. On the second day of your visit, she carries several bags of groceries up two flights of stairs and stops with a pained expression on her face. When you press her to tell you what is wrong, she admits that she is having chest pain. She says that the pain feels as if something is squeezing her chest. She is also nauseous and out of breath. She lies down to rest. The discomfort lasts 2 to 3 minutes, after which the pain stops.

When you talk to her about this incident, she admits that for the past year, she has been troubled by a similar periodic squeezing pain in her chest. Sometimes, she can also feel the pain in her neck and shoulders. The pain usually happens after she does something that requires physical exertion: climbs several flights of stairs, does some heavy housework, unloads groceries, so forth. When this happens, she also often feels nauseous, out of breath, and very tired. The pain typically lasts a few minutes and goes away after she rests a while.

Using your chosen website, try to identify the name of the condition your elderly relative suffers from.

7. Imagine that during a hike, you are bitten by a tick. A red spot appears and spreads. This is a sign that you have been infected with Lyme borreliosis. A friend recommends starting with an antiviral drug (a remedy for viral infections) immediately, since Lyme disease can have very unpleasant consequences, especially when treatment starts too late! Answer the following question using your chosen website:

Does this website provide any information to help you make a decision as to whether or not it is a good idea to start an antiviral treatment?

A. Yes. B. No. C. No information.

Appendix B

Measurement Items

Perceived benefit (PB) (Bhattacherjee and Premkumar, 2004)

PB1: Using this website can be of benefit to me in managing my health.

PB2: Using this website can improve my performance in managing my health.

PB3: Using this website will be useful for my health.

PB4: Using this website can enhance my effectiveness in managing my health.

Trust in provider (TRP)

TRB1: (Benevolence) I expect that this website information provider has good intentions toward me (Hwang and Lee, 2012).

TRB2: (Benevolence) I expect that this website information provider is acting in my best interest (Thatcher et al., 2013).

TRB3: (Benevolence) I expect that this website information provider is well-meaning (Hwang and Lee, 2012).

TRI1: (Integrity) This website information provider is truthful in its dealings with me (Thatcher et al., 2013).

TRI2: (Integrity) I would characterize this website information provider as honest (Thatcher et al., 2013).

TRI3: (Integrity) This website information provider would keep its commitments to deliver quality information (Thatcher et al., 2013).

TRI4: (Integrity) This website information provider is sincere and genuine (Thatcher et al., 2013).

TRA1: (Ability) I believe this website information provider is effective in assisting me to search for health information (Thatcher et al., 2013).

TRA2: (Ability) This website performs its role of health information provider very well (Thatcher et al., 2013).

TRA3: (Ability) Overall, this website is a capable and proficient provider of health information (Thatcher et al., 2013).

TRA4: (Ability) In general, this website is a very knowledgeable provider of health information (Thatcher et al., 2013).

Perceived risk (PR)

RPE1: (Performance risk) The health information site is risky, because it may fail to deliver what it promises (Sun, 2014).

RPE2: (Performance risk) The health information site is risky, because it may provide incorrect information (Lee, 2009).

RPE3: (Performance risk) The health information site is risky, because the information delivered may fail to meet my expectations (Corbitt et al., 2003).

RT1: (Time risk) It may take too much time to find appropriate information on the website (Forsythe et al., 2006).

RT2: (Time risk) Using the website may waste my time (Featherman and Pavlou, 2003).

RPS1: (Psychological risk) The thought of using the health information site makes me feel psychologically uncomfortable (Liao et al., 2010).

RPS2: (Psychological risk) The thought of using the health information site gives me an unwanted feeling of anxiety (Liao et al., 2010).

RPS3: (Psychological risk) The thought of using the health information site causes me to experience unnecessary tension (Liao et al., 2010).

Behavior intention (BI) (Bhattacherjee and Premkumar, 2004)

BI1: I intend to continue using this website to obtain health information.

BI2: I plan to continue using this website to obtain health information.

BI3: I will continue using this website to obtain health information.

Self-efficacy (SE) (Hsu and Chiu, 2004)

SE1: I feel confident exchanging messages with other users in an online discussion.

SE2: I feel confident chatting on the Internet.

SE3: I feel confident downloading files from the Internet.*

SE4: I feel confident creating a web page on the Internet.

* dropped following initial PCA

Perceived severity (PSE) (Ng et al., 2009)

PSE1: Not having access to health information is a serious problem for me.

PSE2: Suffering a loss by not having access to health information is a serious problem for me.

PSE3: Without access to health information, my daily life could be negatively affected.

Perceived susceptibility (PSU) (Goonawardene et al., 2013)

PSU1: My general health is in bad condition.

PSU2: My health causes major complications in my life.

PSU3: My health condition may cause difficulties for me.

Appendix C

Cross-loading, Reliability and Validity (N = 353)

	Barrier	Benefit	Efficacy	Intention	Severity	Susceptibility	Trust
AVE	*0.630*	*0.791*	*0.704*	*0.942*	*0.814*	*0.818*	*0.833*
CR	*0.834*	*0.938*	*0.877*	*0.980*	*0.929*	*0.922*	*0.937*
Alpha	*0.711*	*0.912*	*0.790*	*0.964*	*0.885*	*0.889*	*0.900*
BI1	-0.343	0.329	0.139	**0.969**	0.358	0.182	0.571
BI2	-0.323	0.348	0.120	**0.974**	0.378	0.214	0.555
BI3	-0.328	0.323	0.147	**0.970**	0.380	0.234	0.525
SE1	-0.054	0.133	**0.855**	0.110	0.094	0.020	0.115
SE2	-0.053	0.111	**0.868**	0.106	0.059	-0.026	0.123
SE4	0.038	0.052	**0.793**	0.130	0.110	0.089	0.055
RPE	**0.852**	-0.208	-0.016	-0.297	-0.065	0.113	-0.316
RPS	**0.654**	-0.153	0.032	-0.101	0.021	0.258	-0.177
RT	**0.858**	-0.278	-0.047	-0.353	-0.084	0.105	-0.351
PSE1	-0.064	0.114	0.082	0.354	**0.922**	0.350	0.227
PSE2	-0.053	0.092	0.101	0.324	**0.934**	0.316	0.199
PSE3	-0.063	0.104	0.108	0.359	**0.848**	0.254	0.229
PSU1	0.177	0.030	0.080	0.176	0.265	**0.898**	-0.021
PSU2	0.143	-0.038	0.041	0.178	0.295	**0.916**	-0.040

PSU3	0.155	0.091	-0.008	0.225	0.356	**0.900**	0.028
PB1	-0.276	**0.897**	0.110	0.330	0.095	0.046	0.345
PB2	-0.265	**0.914**	0.067	0.326	0.116	0.053	0.358
PB3	-0.227	**0.871**	0.074	0.255	0.094	0.008	0.292
PB4	-0.210	**0.876**	0.159	0.302	0.103	0.012	0.295
TRA	-0.345	0.401	0.112	0.576	0.255	0.031	**0.924**
TRB	-0.288	0.276	0.071	0.459	0.187	-0.044	**0.887**
TRI	-0.373	0.309	0.123	0.505	0.213	-0.022	**0.927**

Table 1

Descriptive Statistics of Respondents' Characteristics (N = 703)

Demographics	**Category**	**N**	**%**
Gender	Male	327	46.5
	Female	376	53.5
Age	18-19	598	85.1
	20-22	83	11.8
	23-25	9	1.3
	>25	13	1.8
Online health information experience	Yes	366	52.1
	No	337	47.9
Choice of online health information service provider	Website 1	286	40.7
	Website 2	389	55.3
	Website 3	27	3.8
	Missing	1	0.1

Table 2

Results of Reliability and Validity of the Construct Items

	Items	**Standardized Loading (N=353 vs. N=703)**		**AVE (353 vs. 703)**		**CR (353 vs. 703)**		**Alpha Value (353 vs. 703)**	
RPE	RPE1	.842	.839	.704	.705	.905	.905	.861	.861
	RPE2	.879	.869						
	RPE3	.832	.842						
	RPE4	.802	.807						
RPS	RPS1	.951	.925	.816	.825	.930	.934	.896	.896
	RPS2	.904	.920						
	RPS3	.853	.880						
RT	RT1	.807	.817	.780	.779	.875	.875	.742	.734
	RT2	.953	.943						
TRB	TRB1	.916	.935	.841	.876	.941	.955	.905	.929
	TRB2	.938	.948						
	TRB3	.896	.926						
TRA	TRA1	.875	.883	.796	.825	.940	.950	.915	.929
	TRA2	.901	.919						
	TRA3	.899	.922						
	TRA4	.893	.909						
TRI	TRI1	.862	.880	.766	.804	.929	.943	.898	.919
	TRI2	.919	.918						
	TRI3	.870	.906						
	TRI4	.848	.882						

Table 3

Construct Correlations (Diagonal bold values are square root of AVE, N = 353)

	Mean (S.D.)	**BI**	**SE**	**RPE**	**RPS**	**RT**	**PSE**	**PSU**	**PB**	**TRA**	**TRB**	**TRI**
BI	4.88 (1.56)	**.971**										
SE	3.95 (1.58)	.139	**.839**									
RPE	3.87 (1.43)	-.297	-.016	**.839**								
RPS	3.00 (1.57)	-.101	.032	.434	**.903**							
RT	3.59 (1.56)	-.353	-.047	.554	.363	**.883**						
PSE	4.10 (1.75)	.385	.108	-.064	.020	-.085	**.902**					
PSU	3.15 (1.71)	.217	.037	.113	.258	.105	.340	**.904**				
PB	5.67 (1.10)	.344	.116	-.208	-.152	-.278	.115	.036	**.890**			
TRA	5.50 (1.03)	.576	.112	-.283	-.148	-.348	.256	.032	.401	**.892**		
TRB	5.60 (1.07)	.459	.071	-.246	-.157	-.264	.187	-.043	.276	.714	**.917**	
TRI	5.37 (1.01)	.505	.123	-.333	-.182	-.340	.215	-.021	.309	.785	.753	**.875**

Note: BI = Behavior intention; SE = Self-efficacy; RPE = Perceived performance risk; RPS = Perceived psychological risk; RT = Perceived time risk; PSE = Perceived severity; PSU = Perceived susceptibility; PB = Perceived benefit; TRA = Trust-Ability; TRB = Trust-Benevolence; TRI=Trust-Integrity.

Table 4

Summary of Results

N = 353			
Hypothesis (path)	Path coefficient	t-Value	Supported
H1	.160	3.773***	Yes
H2	.173	3.745***	Yes
H3	-.163	3.802***	Yes
H4	.106	2.207*	Yes
H5a	.046	1.076	No
H5b	-.004	.065	No
H5c	-.121	2.731**	Yes
H6	.343	6.950***	Yes
H7a	.424	9.442***	Yes
H7b	.365	6.648***	Yes
H7c	-.374	8.249***	Yes
N = 703			
H1	.132	4.123***	Yes
H2	.188	5.922***	Yes
H3	-.178	5.707***	Yes
H4	.153	4.242***	Yes
H5a	.059	1.919	No
H5b	-.010	.195	No
H5c	-.084	2.301*	Yes
H6	.359	10.496***	Yes
H7a	.386	10.562***	Yes
H7b	.340	8.216***	Yes
H7c	-.364	10.707***	Yes

Note: * $p < .05$; ** $p < .01$; *** $p < .001$

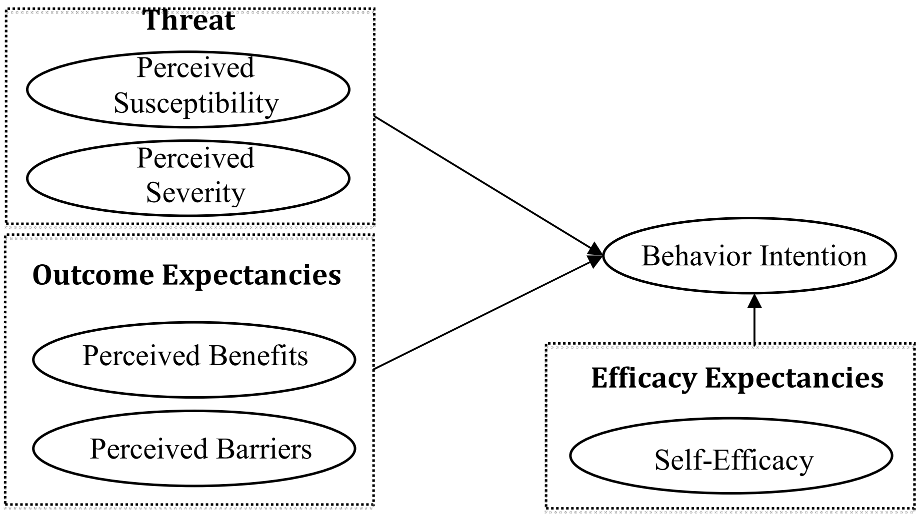

Figure 1. Health Belief Model (Adapted from McKinley and Ruppel 2014)

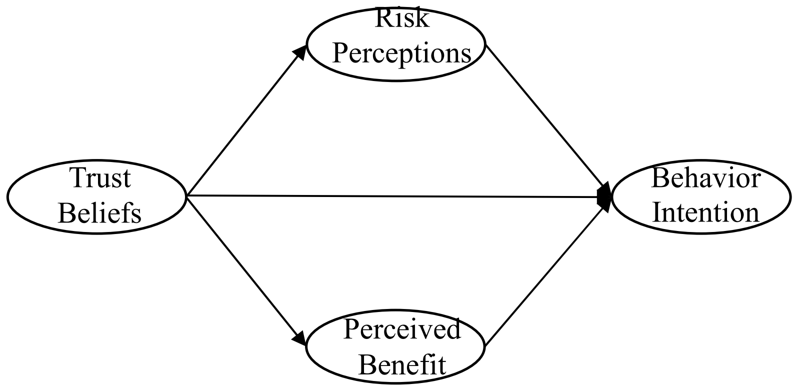

Figure 2. Extended Valence Framework (Kim et al. 2009)

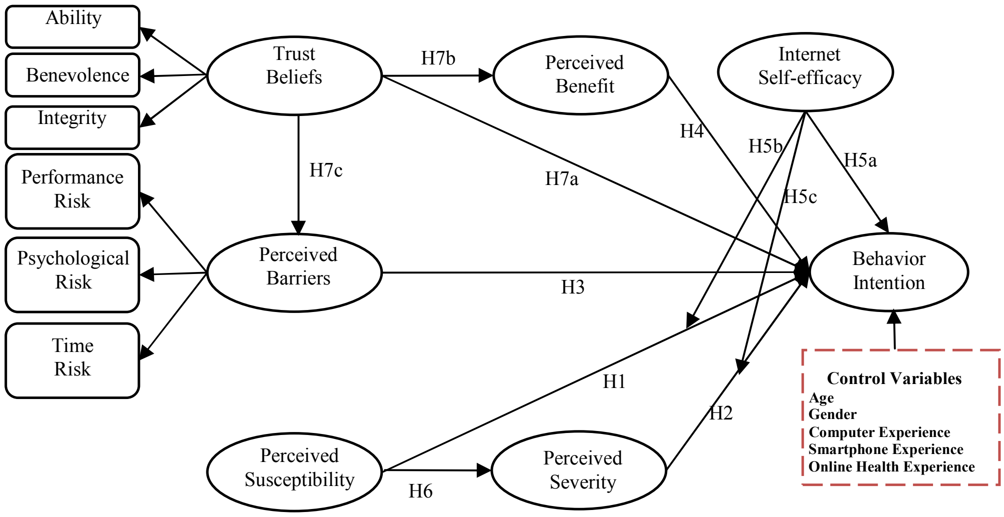

Figure 3. Research Model

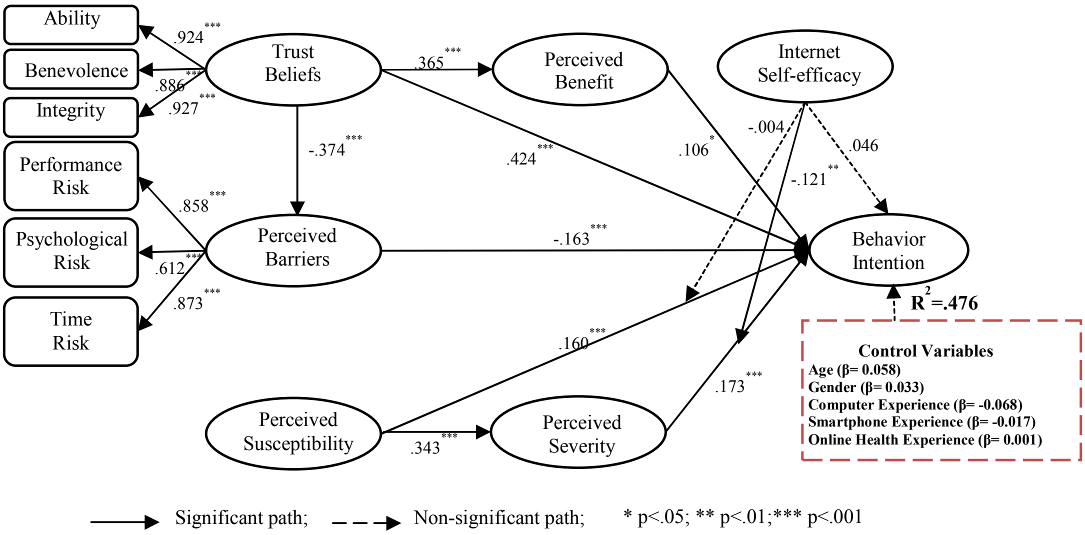

Figure 4. Partial Least Squares Test of Research Model (N = 353; * p < .05; ** p < .01; *** p < .001)