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Abstract:

Purpose

The advancement of technologies has made it possible for healthcare organizations to provide convenient online services that enable people to manage their health conditions. Although many studies have investigated the adoption and benefits of e-Health services, there has been little focus on health-oriented behaviors after adoption, particularly in relation to service quality and user satisfaction.

Design/methodology/approach

This paper is based on the S-O-R model and service quality theories to investigate behavioral responses including word of mouth, intention to use, and intention to act. We utilize a partial least squares structural equation modeling (PLS-SEM) analysis with 194 participants and the diabetes risk test survey in Finland.

Findings

Our results show that people are willing to engage in health self-management behaviors if they intend to use the e-Health service and are satisfied with it. User satisfaction can be enhanced by improving the visual appeal of the website presentation, the quality of the presented information, as well as the usability of the website, all as components of e-Health services.

Originality/value

We contribute by creating a construct "intention to act," referring to health-oriented behaviors resulting from e-Health service use. In addition, our study is among the first to apply the SOR model to investigate how user satisfaction leads to intention to use, intention to act and word of mouth.

Keywords: e-Health; online diabetes test; health self-management; service quality; user satisfaction; word of mouth; intention to use; intention to act.

1. Introduction

Today, there are expanded possibilities for citizens to care for their own health. The Internet offers new ways to understand and manage one's health, using consumer health information technology (CHIT), as an alternative to scheduling face-to-face doctor's consultations (Tao et al., 2020; Leung & Chen, 2019; Sawesi et al., (2016); Weert et al., 2016). Researchers have investigated the effects of online health self-management services, such as MyData-based preventive eHealth services (Kovimaki et al., 2017) and internet-based medical self-diagnosis applications (Lanseng & Andreassen, 2007). However, encouraging consumers to participate in self-health management is a challenging task for e-Health providers and health policy makers (Deng and Liu, 2017; Kovimaki et al., 2017; Leung & Chen, 2019)

Transformative effects can be observed among individuals who utilize health-related websites, where benefits are realized through specific actions taken based on the information obtained. One such action is the "intention to act," whereby users modify their behavior to adopt healthier practices based on advice provided by the website or self-assessment tools. However, existing studies have predominantly focused on users' *intentions* to use CHIT services (Tao et al., 2020) despite the primary goal of CHIT tools to drive *observable* behavioral changes (Sawesi et al., (2016); Weert et al., 2016).

Particularly, while previous studies have primarily examined the impact of these services on online behavioral intentions, there has been limited exploration of how users' online interactive experiences influence their offline behavioral. This research gap highlights the need for further investigations into the relationship between users' online interactions and subsequent offline behavioral intentions and actions within the context of CHIT. To address this research gap, this study aims to examine the factors associated with CHIT that motivate users to actively pursue health benefits. The research question of this study focuses on identifying the driving forces that encourage users to act following the adoption of CHIT.

To address this research issue, we applied a Stimulus-Organism-Response (SOR) model (Mehrabian & Russell, 1974) in an e-Health context. This model encompasses the entire process, starting with the Stimulus phase, which focuses on the impact of service quality on the adoption of CHIT. In this stage, we utilized a measurement approach to access the quality of online healthcare services based on e-Service quality and SERVQUAL. For the Organism phase, user satisfaction takes precedence as the primary evaluation criterion. Lastly, the Response phase encompasses the relationships among the intention to use online services, word-of-mouth, and the intention to act. Importantly, this study extends the examination of user online behavior by exploring the influence of online experience on users' offline behavioral intentions. The insights derived from this research provide guidance for improving online services and encouraging users to actively pursue health benefits.

We selected online diabetes risk assessment as our study domain for several reasons. First, the estimated number of adult patients with diabetes in 2017 was 451 million worldwide, and this number is expected to increase to 693 million by 2045 (Cho et al., 2018). In Finland, there is a population of approximately 5.5 million, of which approximately 50,000 have type 1 diabetes, 400,000 have type 2 diabetes and 4,000 children under the age of 15 have diabetes. It is estimated that there are approximately 50,000 undiagnosed cases of type 2 diabetes (Finnish Diabetes Association). Second, the adoption of health self-management tools such as for diabetes type 2 disease is not well understood (Sheon et al., 2017). Third, according to Chobanian et al. (2003), people are particularly interested in self-assessments in the case of diabetes since these tools can foster an awareness of one's diabetic risks and therefore lead to lifestyle changes.

2. Literature Review

The SOR model is one of the better-known theories in environmental psychology (Chopdar & Balakrishnan, 2020) and is applied popularly in many management fields. The SOR model can be applied to the investigation of e-Health service users' internal states and how they are connected to the characteristics of the service, as well as the behavioral responses linked to these internal states. There have been relatively few attempts to utilize the SOR model in e-Health service research. To the best of our knowledge, the few extant studies that apply SOR to e-health are recent, such as the study of Cao et al. (2020) on m-Health application resistance of Chinese elderly people and Goyal et al. (2021) on the adoption of online doctor consultation platforms in India.

In e-Health, the Technology Acceptance Model (TAM) of Davis, 1989, which adapts the Theory of Reasoned Action (TRA) to the context of work-related technology acceptance, has proven to be a valuable explanatory framework for understanding the service adoption in healthcare (Tao et al., 2020). However, previous research in e-Health services, particularly online health self-management lacks robust theories that examine behavioral outcomes comprehensively, often neglecting the cognitive processes that link interventions and behavioral effects (Sawesi et al., (2016); Zhang & Li, 2017). In addition, Blut et al. (2022) have encouraged researchers to explore novel theories that extend the outcomes of technology use and consider the potential contribution of technology to users' well-being. Therefore, in response to the call from Blut et al., (2022); Tao et al., (2020); Sawesi et al., (2016) and Zhang and Li (2017), we utilize the stimulus-organism-response (S-O-R) framework to test our empirical model. Figure 1 illustrates how we utilize the model in the context of our study.

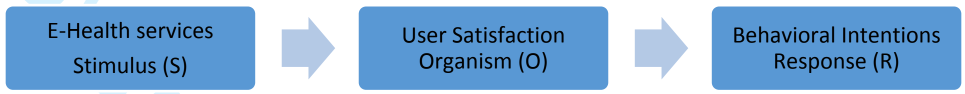

Figure 1. The S-O-R Model

2.1.1. Stimuli

One important stimulus factor in the context of online services is e-Service quality (Blut et al., 2015; Kim & Stoel, 2004; Preaux et al., 2022; Rodriguez et al., 2020; Verma et al., 2020) since it is a feature of the environment (Mari & Poggesi, 2013). In general, the SERVQUAL construct consists of 22 items (Parasuraman et al., 1988) which are grouped into five dimensions: reliability, assurance, tangibles, empathy and responsiveness (Parasuraman et al., 1991). SERVQUAL is one of the most popular service quality scales (Pekkaya et al., 2019).

With the development of online services such as e-Commerce, several researchers have used SERVQUAL to develop the measurement for e-Service quality. Zeitham et al., 2002, designed E-S-QUAL as a multiple-item scale for assessing electronic service quality. Blut et al. (2015) conducted a meta-analytic review and found four underlying dimensions (website design, fulfilment, customer service, and security/privacy) of e-Service quality. However, according to Blut et al. (2015), the quality of e-Services is influenced by industrial characteristics, which act as moderating factors.

Scholars have applied different ways to evaluate e-Health service quality (Preaux et al., 2022; Verma et al., 2020). Preaux et al., 2022 provided the conceptual model to measure the service quality of telemedicine consultation. SERVQUAL has also been applied to study healthcare service quality (Pekkaya et al., 2019). However, researchers have selectively incorporated items that represent the relevant dimensions of interest, instead of relying solely on a single scale from a specific paper (Blut et al., 2015). As the context of health self-help services differs from that of online shopping services, we adjusted SERVQUAL of Parasuraman et al. (1988), E-S-QUAL of Parasuraman et al. (2005), e-Service quality of Blut et al. (2015) and SQ Model of telemedicine service of Preaux et. al. (2022) to the online diabetes test by focusing on the variables of attraction, information quality, emotional support, and perceived ease of use as the critical features for assessing healthcare website quality. Table 1 summarizes the components of our service quality model and compares these components to those of different other service quality models. It indicates which components in other models (shown with "X") inspired the constructs in our model. "No" indicates that the model does not include a component matching our definition. The details of this comparison as well as the definition of each sub-construct can be found in Appendix 1.

Table 1: Explanation of the components of our service quality model in comparison with other service quality models

Components of our service quality model	**SQ Model of Telemedicine Service (Preaux et al., 2022)**	**e-Service quality (Blut et al., 2015)**	**E-S-QUAL (Parasuraman et al., 2005)**	**Traditional SQ (SERVQUAL) (Parasuraman et al., 1988)**
Information Quality	X (Information usefulness)	X (Information Quality)	X (Information at this site is well organized)	No
Attraction (Visual Appeal)	X (Website design)	No	No	X (Tangibles: Visually appealing facilities and visually appealing material associated with services)
Emotional support	X (Empathy)	No	No	X (Empathy)
Perceived Ease of Use	X (Ease of Use)	X (Website convenience)	X (This site makes it easy to find what I need; It makes it easy to get anywhere on the site; The site is simple to use)	No

2.1.2. Organism

We include the concept of customer satisfaction to represent the Organism stage as it refers to the internal state of a user of online services. Some definitions of customer satisfaction have focused on the relationship among customers' expectations and evaluations (Zeithaml et al., 1993) and others on the cognitive and emotional aspects of a customer's perception (Crow et al., 2002). Most customer satisfaction definitions include the three components of psychological, experiential, and expected (Kuske et al., 2000). We define the concept by focusing on customer perception in the context of online healthcare services.

In general, people are less likely to adopt e-Health services if they are dissatisfied with those tools. It is nevertheless a fact that the treatment of many illnesses, particularly those that are chronic, involves significant attention to the subjective well-being of patients. In cases where a disease cannot be effectively cured, but the symptoms may only be managed, patients' satisfaction becomes very important. Hence, as online services gain in prevalence, more research is needed to investigate e-Health service quality and patient satisfaction in online settings (Verma et al., 2021; Yang et al., 2015).

2.1.3. Responses

In the SOR framework, the response is a reaction to individuals' perceptions based on situational factors (Parboteeah et al., 2009). Responses to online e-Health services can consist of a variety of behaviors resulting from the use of those services. These correspond to the outcomes of the organism component variables in the SOR model (Mari & Poggesi, 2013). Particularly, Blut et al. (2015) emphasized the influence of e-Service quality on important outcomes such as repurchase intentions and word-of-mouth. Thus, in this research, we apply three behavioral intention outcomes as the response component of the SOR model, including word-of-mouth, intention to use a service, and intention to act, to carry out behaviors to improve one's health.

3. Hypothesis Development and Research Model

3.1.1. Stimuli and Organism

Attraction (ATR) or visual appeal is defined as the extent to which users find the website well-developed and enjoyable (Bol et al., 2013; Kim & Stoel, 2004; Parboteeah et al., 2009). One can be satisfied with the visual appeal or attractiveness of a website, which relates to the overall design of the website (Bol et al., 2014; Verkijika & Wet, 2019). Chang et al. (2014) proposed that aesthetic appeal reflects the degree of pleasure, satisfaction, and entertainment that users experience from the website. Similarly, Rodriguez et al. (2020) studied fashion e-retailers in Spain and found that hedonic quality, including enjoyment and virtual emotion, had a strong link to customer satisfaction. Thus, we propose that:

H1: Attraction (or visual appeal) is positively associated with satisfaction.

Information quality (INQ) has been found to be an important predictor of satisfaction (Ghasemaghaei & Hassanein, 2015; Kim & Stoel, 2004). As one function of websites is to provide information, it is reasonable for online information quality to be linked to the satisfaction of those using online websites. Indeed, the effect of information quality has been established in the online context (Ghasemaghaei & Hassanein, 2015) and, particularly, in the online health context (Preaux et al., 2022; Verma et al., 2020). Accordingly, we hypothesize that information quality positively promotes user satisfaction, as follows:

H2: Information quality is positively associated with satisfaction.

Emotional support (EMS) is the positive support provided by a website to user emotions and in mitigating stress (Bol et al., 2013; Yan & Tan, 2014). While emotional support originates from communication with other people, websites can be mediators and channels for such communication, and therefore can have an impact upon users (Deng & Liu, 2017). Health-related websites have been found to help people cope with illness and with negative emotions. For example, cancer patients reported finding social support and increased hope after accessing cancer-related websites (Bol et al., 2013). When individuals experience positive emotions, they become more satisfied. This has also been found with health-related websites (Bol et al., 2014; Verma et al., 2021). Verma et al. (2021) reported that quality of interaction, as a part of e-Health service quality, can promote emotional support, leading to patient satisfaction. Thus, we propose that:

H3: Emotional support is positively associated with satisfaction.

Perceived ease of use (PEOU) is a fundamental component of service quality in online settings, such that a user interface influences the benefits derived from a service (Preaux et al., 2022). PEOU includes components such as functionality of the website, consistency of design and navigation, and the smoothness of interactions (Zeithaml et al., 2002). Ease of use, if absent, will hamper consumers' perception of convenience and information availability. When present, however, ease of use can lead to user satisfaction (Verkijika & Wet, 2019) and enhance overall system quality (Jung et al., 2015). Thus, we propose that:

H4: Perceived ease of use is positively associated with satisfaction.

3.1.2. Organism and Responses

Consumers often post rational emotional messages describing their opinions of products. A common view in many studies is that user satisfaction plays an important role in enhancing word of mouth (WOM) (King et al., 2014). This view has support in numerous studies in various contexts (Jung et al., 2015; King et al., 2014). Positive WOM can be seen as a user's way of reciprocating the satisfaction gained from interacting with the product. In the Pauli et al. (2023) literature review on WOM in the healthcare sector, they noted the impact of patient satisfaction on generating positive word-of-mouth (WOM). So, we hypothesize that:

H5: Satisfaction is positively associated with WOM.

The role of satisfaction as a critical predictor of intention has been well-established in the information systems, management, and marketing related reference disciplines (Akter et al., 2013; Chopdar & Balakrishnan, 2020; Jung et al., 2015). Satisfaction is also important for healthcare interventions, particularly in the context of online health tools (Akter et al., 2013; Yang et al., 2015). If the users of health websites are satisfied, they are then positively inclined to use the websites. Xing et al. (2020) reported that satisfaction has a positive impact on the intention to engage in online consultations. Hence, we hypothesize that:

H6: Satisfaction is positively associated with intention to use.

One objective of e-Health is to influence users' behaviors in a positive way. It has been found that online experience does influence peoples' actual activity intentions (Xing et al., 2020). Xing et al. (2020) demonstrated that a satisfactory online consultation positively influences the patient's intention to seek face-to-face consultations. People who are satisfied with online health information can be expected to receive positive health outcomes. Enwald et al. (2012) found that 70% of people with a high risk of diabetes were willing to change their dietary habits to improve their health condition after searching online health information. In general, using online e-Health services can lead to increased self-care for diabetes patients (Jamal et al., 2015). Thus, we propose this hypothesis:

H7: Satisfaction is positively associated with intention to act.

According to dissonance theory, individuals seek harmony between their attitudes and behaviors by mitigating inconsistencies that may exist between these two (Valkenburg, 2017). An individual will be motivated to change their behavior, particularly if they have publicly committed to their attitude and this inconsistency is pointed out by others (Stone & Fernandez, 2008). Hence, word of mouth, as a public commitment, should promote consistent actions. In the healthcare context, Nabi et al. (2019) found that sharing health-related information such as a video clip makes it more likely that the individual sharing this information will practice health-oriented behaviors. Thus, we hypothesize:

H8: Word of mouth is positively associated with intention to act.

The use of a system is often evaluated based on improvements in work performance or increased online product purchases. Previous studies, primarily conducted in the retail industry, suggest that patients' online perceptions can influence their offline behavioural intentions (Xing et al., 2020). However, in an e-Health context, there are limited studies exploring the relationship between "intention to use" and "intention to act." Hamari and Koivisto (2015) discovered a positive association between continued use intentions of Fitocracy, an online gamified exercise platform, and continued exercise intentions. Xing et al. (2020) found that online consultation serves as a means of interacting with health professionals and influencing patients to seek further medical advice. The intention to actively manage one's health based on the information obtained through online tools is a desirable and expected outcome of utilizing such resources to derive health benefits. Thus, intention to act is hypothesized to increase as a behavioural outcome of intention to use.

H9: Intention to use is positively associated with intention to act.

3.2. Research Model

Figure 2 presents the research model. We map each of the nine hypotheses into one of the direct paths in the model.

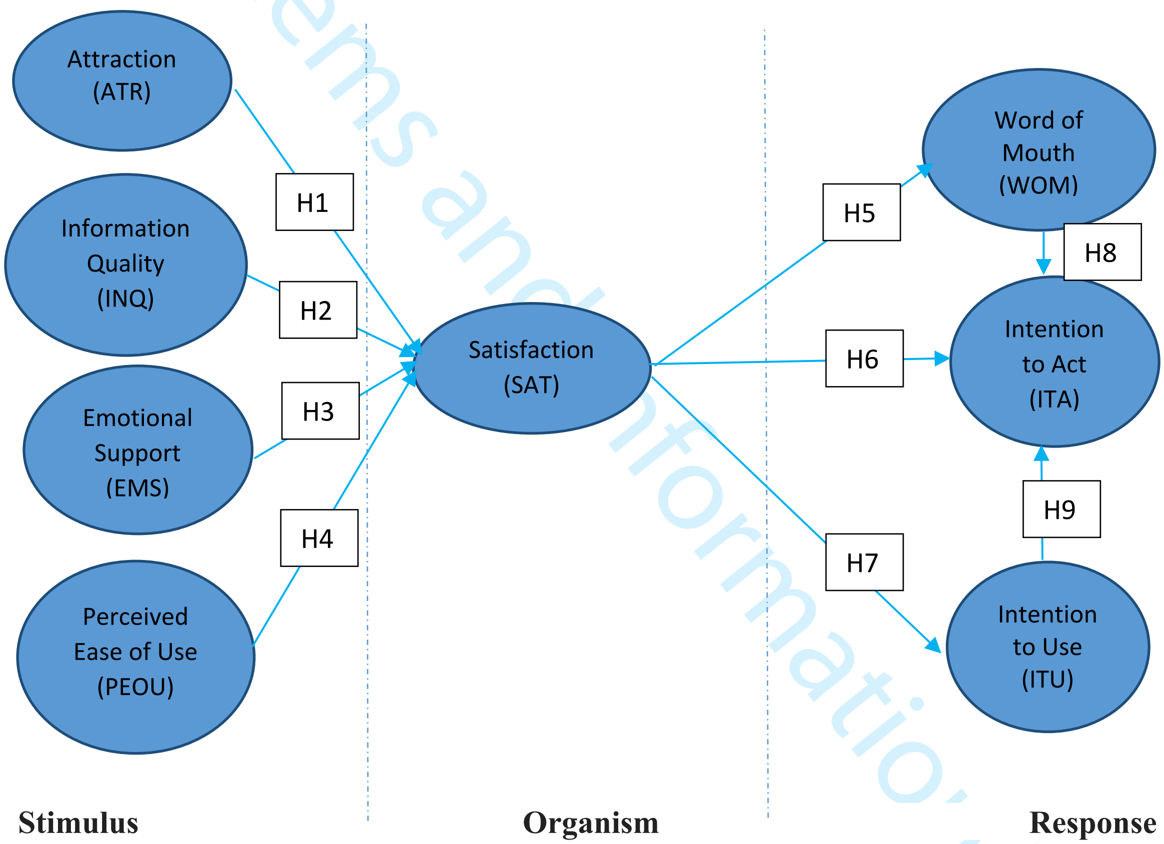

Figure 2. Research Model

4. Research Method

4.1. Development of measurement tools

The research method utilized a questionnaire focusing on the user experience and related health behaviors associated with an online diabetes risk test in Finland. The questionnaire was available in three languages: Finnish, Swedish, and English, and included questions soliciting demographic background information.

Most of the constructs in the research model except “intention to act” were adapted from previous studies to fit this study’s context (see Appendix). “Intention to act” reflects the participants’ health-directed behaviors toward diabetes risk management. We developed this construct based on reviewing previous diabetes studies. Using the most frequently occurring Internet search words accompanying diabetes (Kuske et al., 2017; National Diabetes Statistics Report, 2020), which are 'diet', 'complications', 'exercise' and 'medications and pharmacological interactions.' we built the construct of "intention to act" (see Appendix). Other than face validity, the reliability and validity of "intention to act" was ensured by following the same steps as taken with all the other measurement items and structural model constructs. This specific process is detailed in section 5. Data Analysis and Results. Two initial intention to act measurement items were removed because they loaded on their respective latent construct at a value less than 0.707 as prescribed by Hair et al. (2014).

All items were measured with a Likert scale of five points (from 1 = totally disagree to 5 = totally agree). A pre-test of the questionnaire was completed with four individuals who had experience using e-Health services. These individuals were asked to evaluate the extent to which the terms in the instrument were appropriate and clearly understandable. As a result, the questionnaire was slightly revised in terms of rewording the questions related to the respondents' background, and their user experience and behavior. The final questionnaire with detailed scale items and their references is available in Appendix 2.

4.2. *Sample collection*

The data were collected online using Webropol (www.webropolsurveys.com) over a period of ten months. Potential participants were identified as individuals who were interested in being informed about their risk of having or developing type 2 diabetes, one of the most widespread diseases in Finland (Finnish Diabetes Association, 2017). We posted our survey next to the diabetes risk test on the website of the association (https://www.diabetes.fi/riskitesti). This was useful as more than a quarter (26.76%) of the respondents indicated that they found the survey when searching for information on diabetes. To reach an even wider audience, we sent out a university press release and asked our colleagues to circulate a link to the survey. All participants were asked to complete the diabetes risk test before responding to our survey.

We received 204 responses, but 6 responses were eliminated because of missing values, leaving a total of 198 remaining valid responses. The majority (nearly 68%) of the respondents were female. This is reflective of the fact that women more often utilize online tests and risk tests (Kauer et al., 2014). The mean age of the respondents was 58.64 years old, and more than 80% of the sample were at least 45 years old, which reflects that people who are 45 or older are more likely to develop diabetes (Kahn et al., 2009). More than 80% of the sample used the Internet daily, thus mitigating the issue of a 'digital divide' characterizing our aging population (Heponiemi et al., 2020; Or & Karsh, 2009). Approximately 50% of the participants had a bachelor's or advanced degree.

4.3. *Data Analysis Methods*

We used the partial least squares structural equation modeling (PLS-SEM) technique to estimate the impact of the stimulus and organism variables upon the response variables (Joreskog & Wold, 1982). A path modeling approach was chosen as we wanted to evaluate and assess the simultaneous influence of multiple cascading independent and dependent latent variables. A variance-based approach (PLS-SEM) was selected instead of a covariance-based technique (i.e., CB-SEM) for three reasons. According to Hair et al. (2014) the PLS-SEM technique is preferred over CB-SEM when: 1) the goal is to predict key "target" constructs or to identify key "driver" constructs; 2) the structural model is relatively complex (with many constructs and many indicators) and 3) the data are non-normally distributed. A Jarque-Bera test of normality (1980) conducted on our data indicated non-normal distributions for the latent variable scores in ATR, PEOU, SAT, WOM, ITA and ITU. PLS-SEM estimates maximize the explained variance of the latent dependent variables, in our case, the predicted (endogenous) latent variables SAT, WOM, ITA and ITU through an iterative algorithm based on ordinary least squares (OLS). The PLS-SEM model consists of two parts: an outer, or measurement model, and an inner, or structural model, estimating the hypothesized relationships among the latent variables. The outer model assesses the relationships of the latent constructs with their respective indictor manifest variables as composite indices, and the inner model estimates the relationships among the latent variables themselves. To conduct the analysis, we used WarpPLS software version 8.0, developed by ScriptWarp Systems in the U.S. (Kock, 2022).

5. Data Analysis and Results

5.1. Measurement (outer) model

We used the guidelines published by both Henseler et al. (2016) and Hair et al. (2019) in evaluating both the measurement and structural models. We evaluated the measurement model by assessing the internal consistency (composite reliability), indicator reliability, convergent validity, and discriminant validity. Table 2 reflects the reliability results for the measurement part of the model: composite reliability (with all values above the 0.70 threshold) (Nunnally, 1978); average variance extracted (with all values above the 0.50 threshold); and Cronbach's alpha coefficients (with all values above the 0.70 threshold). All measures show adequate levels of internal consistency.

Table 2. Assessment of the measurement model.

Variable	Composite reliability (D.G. rho)	Average variance extracted (AVE)	Cronbach's alpha coefficients
ATR	0.88	0.64	0.81
INQ	0.86	0.62	0.79
EMS	0.94	0.79	0.91
PEOU	0.94	0.80	0.92
SAT	0.94	0.78	0.91
WOM	0.93	0.78	0.91
ITA	0.82	0.53	0.71
ITU	0.88	0.59	0.83

Tables 3 and 4 further inform about the discriminant validity of the measurement scales. Table 2 reflects the commonly used Fornell Larcker (1981) test of discriminant validity. In table 3, the bolded diagonal indicates the square roots of the AVEs, which are higher in all cases than the off-diagonal elements in their corresponding row and column, thus verifying the discriminant validity of the scales. Additionally, since none of the off-diagonal correlations exceed the recommended threshold value of 0.8 (Kennedy, 2003), we retained all latent variables in the model.

Table 3. Discriminant validity: Fornell Larcker Criterion.

Variable	ATR	INQ	EMS	PEOU	SAT	WOM	ITA	ITU

ATR	**0.80**							
INQ	0.33	**0.79**						
EMS	0.42	0.56	**0.89**					
PEOU	0.42	-0.04	-0.02	**0.89**				
SAT	0.71	0.42	0.42	0.39	**0.89**			
WOM	0.55	0.45	0.41	0.24	0.71	**0.88**		
ITA	0.37	0.36	0.37	0.19	0.40	0.37	**0.73**	
ITU	0.55	0.46	0.41	0.25	0.69	0.73	0.50	**0.77**

Table 4 reports the heterotrait-monotrait (HTMT) ratios of correlations among the latent variables. The HTMT approach was first introduced by Henseler et al. (2015) as an alternative, and more reliable approach, compared to the Fornell-Larcker criterion (1981), to demonstrate the discriminant validity of latent variables in a reflective composite model. As indicated in table 3, all off-diagonal HTMT ratios are well below the recommended 0.85 threshold (Henseler et al., 2015) needed to demonstrate the discriminant validity of the latent variables.

Table 4. Discriminant validity: HTMT ratios.

Variable	ATR	INQ	EMS	PEOU	SAT	WOM
ATR						
INQ	0.432					
EMS	0.495	0.669				
PEOU	0.481	0.114	0.109			
SAT	0.829	0.508	0.473	0.431		
WOM	0.643	0.538	0.458	0.268	0.787	
ITA	0.497	0.478	0.461	0.249	0.501	0.471
ITU	0.674	0.564	0.476	0.289	0.790	0.839

An additional technique to demonstrate both discriminant and convergent validity in the measurement model is to examine the loadings and cross-loadings of all measurement items with their respective (and non-respective) latent variables. Table 5 reflects the combined loadings (bolded) and cross-loadings of all indicator items to the latent constructs. The range of loadings is within the interval 0.72-0.95, each higher than the recommended threshold of 0.708, with the exceptions of INQ4 at 0.65 and ITA4 at 0.68. However, we retain INQ4 and ITA4 as indicators for their respective latent constructs, using guidance provided by Hair et al. (2014). Also, in all cases, the loading of a measurement item with its own respective construct greatly exceeds the respective cross-loadings with the other non-respective constructs. These indicator loadings and cross-loadings again demonstrate the discriminant (and convergent) validities of the measurement model.

Table 5. Discriminant (and convergent) validity: Loadings and cross-loadings.

	ATR	INQ	EMS	PEOU	SAT	WOM	ITA	ITU
ATR1	**0.72**	0.23	0.09	-0.04	-0.11	0.30	-0.10	-0.21
ATR2	**0.86**	-0.12	-0.03	-0.06	0.01	-0.16	-0.06	0.12
ATR3	**0.78**	-0.09	-0.10	0.19	0.10	-0.13	0.16	0.03
ATR4	**0.83**	0.01	0.05	-0.08	0.00	0.03	-0.01	0.02
INQ1	-0.08	**0.75**	-0.08	0.06	-0.05	-0.01	0.05	0.28

INQ2	-0.09	**0.84**	0.02	-0.02	-0.10	0.03	0.00	0.10
INQ3	0.05	**0.88**	-0.06	-0.06	0.01	-0.16	0.02	0.00
INQ4	0.14	**0.65**	0.14	0.04	0.17	0.19	-0.08	-0.46
EMS1	0.01	0.15	**0.90**	0.02	-0.03	-0.19	0.02	0.08
EMS2	0.06	0.09	**0.91**	-0.04	-0.19	0.15	0.00	-0.13
EMS3	-0.10	-0.06	**0.92**	-0.06	0.15	0.02	0.03	-0.05
EMS4	0.04	-0.19	**0.83**	0.09	0.08	0.03	-0.05	0.12
PEOU1	-0.03	0.07	0.06	**0.90**	0.04	-0.05	-0.14	-0.01
PEOU2	-0.06	-0.02	0.01	**0.95**	0.02	0.08	0.01	-0.03
PEOU3	-0.02	-0.02	0.03	**0.85**	0.07	-0.02	0.17	-0.10
PEOU4	0.11	-0.03	-0.11	**0.87**	-0.12	-0.01	-0.03	0.14
SAT1	0.36	0.03	0.01	-0.07	**0.80**	0.11	0.04	-0.13
SAT2	-0.06	-0.05	0.01	-0.02	**0.92**	-0.01	-0.11	0.03
SAT3	-0.11	-0.02	-0.04	0.04	**0.92**	-0.08	-0.03	0.11
SAT4	-0.15	0.05	0.02	0.05	**0.89**	0.00	0.10	-0.02
WOM1	0.11	-0.08	-0.10	0.00	0.27	**0.85**	0.09	-0.11
WOM2	-0.10	-0.03	-0.02	0.06	0.22	**0.89**	-0.07	0.06
WOM3	-0.01	0.05	0.03	0.02	-0.28	**0.91**	-0.04	-0.04
WOM4	0.01	0.06	0.08	-0.07	-0.20	**0.89**	0.02	0.08
ITA1	-0.02	0.06	-0.22	0.00	0.26	-0.35	**0.76**	0.21
ITA2	0.00	-0.05	0.11	0.01	-0.52	0.48	**0.73**	0.03
ITA3	-0.13	0.02	0.10	-0.05	-0.01	-0.02	**0.75**	-0.08
ITA4	0.16	-0.04	0.02	0.05	0.27	-0.10	**0.68**	-0.17
ITU1	-0.07	0.19	-0.24	-0.06	0.35	-0.05	-0.16	**0.80**
ITU2	-0.13	0.10	0.01	-0.03	0.01	-0.04	-0.09	**0.82**
ITU3	-0.21	-0.11	0.24	-0.06	-0.24	0.23	0.06	**0.74**
ITU4	0.21	-0.12	0.03	0.10	-0.14	-0.15	0.09	**0.76**
ITU5	0.22	-0.09	-0.03	0.05	-0.01	0.02	0.12	**0.73**

5.2. Structural (inner) Model

The structural equations model was estimated using the Warp 3 procedure with WarpPLS 8.0 (Kock, 2022). We present descriptive statistics of the normalized values for the minimum, maximum, and median values for each latent variable construct in table 6 below.

Table 6. Descriptive statistics of latent variable values.

	ATR	INQ	EMS	PEOU	SAT	WOM	ITA	ITU
Minimum:	-1.875	-2.295	-2.252	-0.693	-1.457	-1.590	-1.500	-2.019
Maximum:	3.678	3.151	2.020	4.693	3.759	2.996	4.190	3.361
Median:	-0.133	0.047	-0.116	-0.093	-0.153	-0.149	-0.078	-0.135

We checked for multicollinearity and found that all VIF values were lower than 3.0, below the recommended threshold of 5. In terms of goodness of fit, the standardized root mean square residual (SRMR) is 0.10, equal to the maximum acceptable threshold value of 0.10 (Hu and Bentler, 1999). Furthermore, the calculated cross-validated redundancy (Q2) values for the endogenous latent variables are: SAT = 0.538; WOM: 0.513; ITA = 0.268; and ITU = 0.481. Q2 values larger than zero indicate predictive relevance for the structural model endogenous constructs (Hair et al., 2014).

Finally, we conducted two tests to detect the presence of Common Method Bias (CMB). We inspected the full collinearity variance inflation factors (FCVIFs) (Kock, 2015) in the WarpPLS software output, and we performed Harman's single-factor test with principal components (Schwarz et al., 2017). Both tests failed to detect any common variation in the latent variable scores which could be attributable to a CMB source.

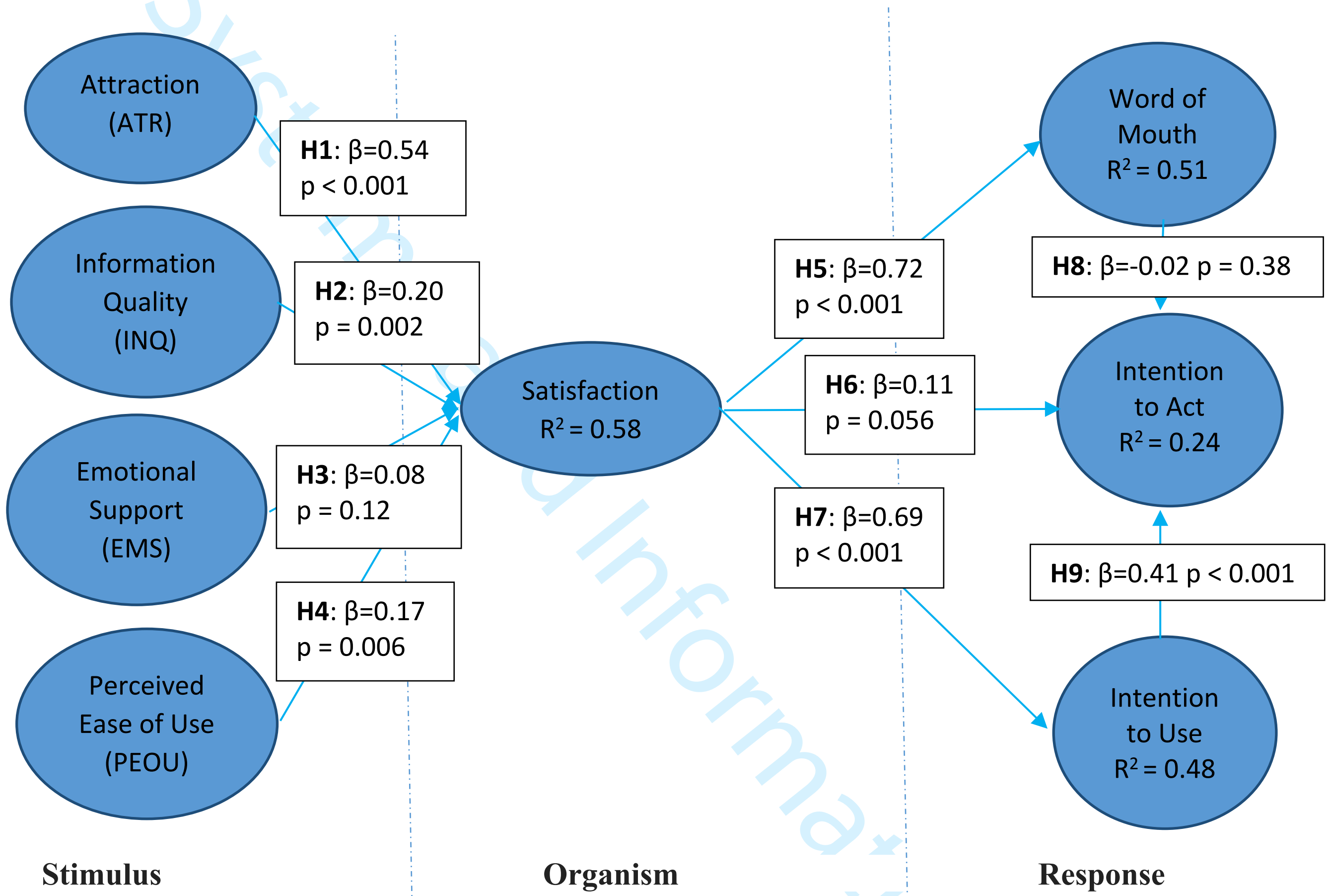

Figure 3. Research model results.

Figure 3 shows the results for the estimated structural (inner) research model. Specifically, figure 3 indicates the estimated beta path coefficient estimates and R^2 values for the endogenous variables. Additionally, the significance levels for the estimated path coefficients are indicated. The estimated path coefficients corresponding to the hypothesized direct effects are all positive (as hypothesized) and significant (with the exceptions of H3 and H8). In the research model results, the highest level of explained variance, $R^2 = 58.4\%$, is for the endogenous variable satisfaction. The levels of variance explained in the other three endogenous variables are: word of mouth (51.2%), intention to act (23.9%), and intention to use (48.1%) respectively.

Figure 4 presents the direct path effect sizes for each hypothesis visually mapped into the research model. According to Cohen's (1988) guidelines, $f^2 \geq 0.02$, $f^2 \geq 0.15$, and $f^2 \geq 0.35$ represent small, medium, and large effect sizes, respectively. It can be seen from figure 4 that the direct path links in the research model from ATR to SAT (H1), SAT to WOM (H5), and SAT to ITU (H7) each represents large effect sizes. The direct path from ITU to ITA (H9) represents a medium effect size. However, the direct path links from INQ to SAT (H2), EMS to SAT (H3), PEOU to SAT (H4,) and SAT to ITA (H6) each represent small effect sizes. There is evidently no effect along the direct path link from WOM to ITA (H8). Occasionally, in PLS-SEM studies with very large population sample sizes, the relative magnitudes of effect sizes may differ from the relative magnitudes of the estimated beta direct path coefficients, requiring additional explanation about these divergent findings. However, in this study they are consistent.

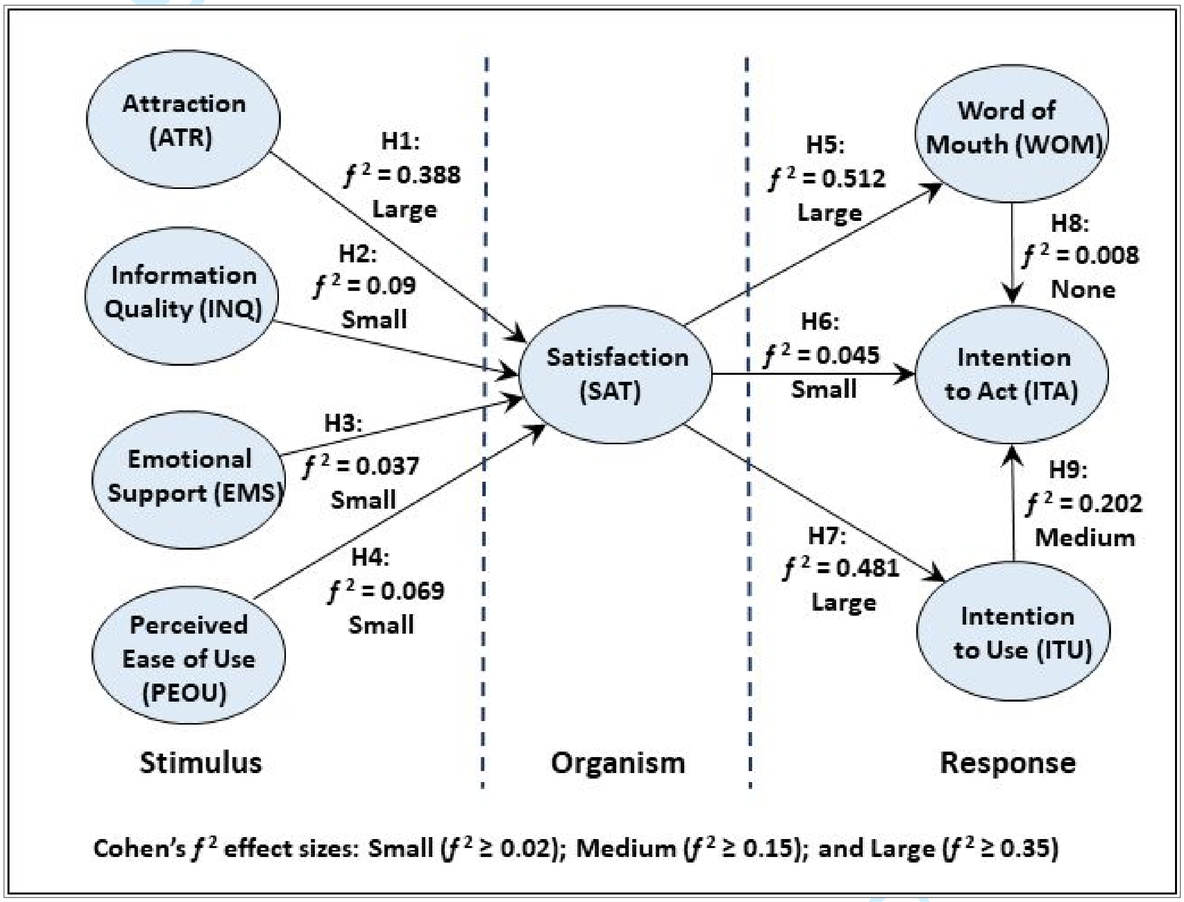

Figure 4. Research model with hypotheses direct paths effect sizes

Table 7 presents a summary of our findings with respect to each of the original hypotheses. The hypotheses were accepted or rejected based on the direction (+ or -) and the significance levels of each of the nine structural paths corresponding to each hypothesis (see figure 3). Generally, our findings are consistent with the nine hypotheses with the exceptions of hypotheses H3 and H8. Attraction has a significant positive effect on satisfaction (H1, $\beta = 0.54$, $p < 0.001$). Information quality has a significant positive effect on satisfaction (H2, $\beta = 0.20$, $p = 0.002$). Emotional support does not have a significant positive effect on satisfaction (H3, $\beta = 0.08$, $p = 0.12$). Perceived ease of use has a significant positive effect on satisfaction (H4, $\beta = 0.17$, $p = 0.006$). Furthermore, satisfaction has a significant positive direct effect on word of mouth (H5, $\beta = 0.72$, $p < 0.001$); a (one-tailed) positive effect on intention to act (H6, $\beta = 0.11$, $p = 0.056$); and a positive effect on intention to use (H7, $\beta = 0.69$, $p < 0.001$). Finally, word of mouth does not have a positive effect on intention to act (H8, β = 0.02, p = 0.38) and intention to use has a significant positive direct effect on intention to act (H9, β = 0.41, p < 0.001).

Table 7. Summary of findings with respect to hypotheses

Hypotheses	Findings
H1: Attraction is positively associated with satisfaction	Supported
H2: Information quality is positively associated with satisfaction	Supported
H3: Emotional support is positively associated with satisfaction	Not supported
H4: Perceived ease of use is positively associated with satisfaction	Supported
H5: Satisfaction is positively associated with WOM intentions	Supported
H6: Satisfaction is positively associated with intention to act	Supported
H7: Satisfaction is positively associated with intention to use	Supported
H8: WOM is positively associated with intention to act	Not supported
H9: Intention to use is positively associated with intention to act	Supported

6. Discussion

6.1. Intention to act is contingent on intention to use and satisfaction.

In our study, user satisfaction had a large f^2 effect size (Cohen, 1988) on WOM (0.512), as well as on ITU (0.481). Thus, our study confirmed the positive link between user satisfaction to ITU, which has been examined before in the healthcare context (Akter et al., 2013; Xing et al., 2020). Numerous prior studies, particularly those conducted in the retail sector (Blut et al., 2015), have also examined the link between satisfaction and WOM. However, this study is one of the first to investigate the connection between satisfaction and WOM specifically in the healthcare domain. By identifying e-Health quality services as key factors influencing patient satisfaction, this study underscores the significant impact that patient satisfaction can have on generating positive WOM.

Moreover, our research found that intention to use and satisfaction with e-Health services directly influence actionable plans for health self-management based on the results of the online diabetes risk test. Our results are in line with past studies (Enwald et al., 2012; Jamal et al., 2015; Xing et al., 2020), arguing that patients' online perceptions influence their offline behavioral intentions.

Previous studies have primarily focused on the impact of WOM from senders on the behavioral intentions of WOM receivers (Martin, 2017; Pauli et al., 2023). However, this study takes a unique approach by investigating the impact of WOM from senders on their own intentional behaviors. Contrary to the finding of Nabi et al. (2019), our study found no direct link between WOM and intention to act in terms of changing health behavior. The intention to recommend the test to others may be driven by social norms or perceived expectations (Martin, 2017; Pauli et al., 2023), where individuals feel it is socially desirable to promote the test but may not have the same personal commitment to change their own behavior. In addition, people may only talk about the service to others if they have friends or acquaintances who are at high risk for diabetes and might benefit from the service (strong ties) (Martin, 2017). And it is essentially random whether users happen to have these kinds of friends and acquaintances. Therefore, it is sensible that WOM is disconnected from one's own health-oriented behaviors.

6.2. What do we need to satisfy e-Health users?

Sources of satisfaction can significantly differ for different product and service offerings (Verkijika & Wet, 2019). In the context of e-Health, our study shows that determinants of e-Health user satisfaction include attraction (visual appeal), information quality, and usability (perceived ease of use), but not emotional support. These variables explain more than 58% of the variance in satisfaction (Figure 3). In the area of e-Health, ease of use and usability issues have been poorly addressed in the past (Sheon et al., 2017). Our results underscore that ease of use remains an important issue for e-Health and especially for health self-management websites and apps.

In e-Healthcare services, the doctor's diagnosis can be replaced by a self-diagnosis based on the online information; and hence, information quality can be expected to be a critical factor. Our results are consistent with the findings of Preaux et al. (2022), who show that website content and technical adequacy predict satisfaction with telemedicine consultation, and with Verma et al., (2020), who show that interaction quality including information impacts online services satisfaction in healthcare domains.

We also consider visual appeal as a component of online service quality and find that it strongly impacts the satisfaction of e-Health service users. There are precedents that show that the visual appeal of a product promotes satisfaction, for example in online shopping (Chang et al., 2014). Similar results are available in studies in online healthcare, showing that website attractiveness (Bol et al., 2013) and the visual elements of a health app (Biduski et al., 2020) promote positive experiences and directly or indirectly influence user satisfaction.

Lastly, contrary to our expectations, our research did not find that emotional support promotes user satisfaction. In healthcare quality studies, emotional support or empathy is recognized as a crucial criterion that defines the quality of healthcare services (Preaux et al., 2022). However, when it comes to health prevention solutions, users may experience increased stress due to the passive nature of their motivation. While they are motivated to use these solutions for disease prevention, their motivation is not active, but rather reactive. This passive motivation can lead to feelings of stress and hinder their ability to enjoy the service. Consequently, they may not consider emotional support as a contributing factor to the overall service quality in satisfying them as found in our study.

7. Contribution

7.1. Theoretical contribution

One theoretical contribution of this study is the applicability of the SOR framework in identifying the antecedents and consequents of user satisfaction in e-Health services. Our study responds to the call for exploring novel theories that expand our understanding of the potential impact and outcomes of technology on users' well-being (Blut et al., 2022; Tao et al., 2020; Sawesi et al., 2016; and Zhang and Li, 2017). The findings suggest that future research could further enhance the literature on e-Health services by employing the SOR framework in addition to established theories such as sociodemographic factors (Or & Karsh, 2009) or the Technology Acceptance Model (TAM) (Davis, 1989).

In the Stimulus phase, we considered e-Service quality as the external environment which will trigger a person's internal state (usually cognition or affect) in the second organism phase. While three items (i.e., information quality, perceived ease of use and visual appearance) of e-Service quality were found to have an impact on users' satisfaction, emotional support did not enhance the satisfaction level of e-Health service users in our study. This raises the question regarding the role of this item in measuring the e-Health service quality even though emotional support or empathy is a dimension within the SERVQUAL framework (Parasuraman et al., 1988).

Our study highlights the significance of satisfaction as a pivotal internal factor in the organism stage of the SOR model that influences behavioral responses. It is important to note that high levels of satisfaction are crucial for enhancing behavioral intentions. It also serves as a mediating factor between the antecedent stimuli and the outcomes in the model. In future research, adopting the SOR model can provide valuable insights into bridging the user's experience with their behavioral intentions.

In the last phase (response stage of SOR), our study contributes to the literature by creating an "intention to act" construct which represents the actual motivation for behavioral change from using e-Health services. Furthermore, this study contributes to the existing literature by examining the link between intentions to adopt e-Health services and intentions to change health behaviors, as related to the outcomes of online services. Our interrelated influence model can serve as a foundation for future studies to investigate various types of online behavior intervention services such as obesity prevention or mental consultation services.

7.2. Practical contribution

Based on our findings, users' intentions to utilize e-Health services have a direct impact on motivation to improve health behaviors. When people exhibit a willingness to engage with e-Health, they are more likely to demonstrate a stronger intention to actively pursue their health benefits, such as changing their diet behavior or seeking appointments. Consequently, it becomes important to prioritize user satisfaction to encourage the adoption of e-Health services and to thereby foster a greater likelihood of proactive self-health management behaviors.

Therefore, e-Health providers should focus on the factors that positively impact user satisfaction. This includes presenting information in a visually appealing manner that captures the user's attention. It is also important for e-Health service providers to ensure that their online interventions meet the criteria for consumer health information. These include providing evidence-based information, incorporating interactive elements, and citing referenced resources with qualified authors to ensure the reliability and validity of health information. By addressing these aspects, e-Health providers can contribute to user satisfaction and ultimately achieve desired behavioral outcomes.

Finally, our research suggests that users of health prevention solutions may fail to act due to the passive nature of their motivation. While individuals acknowledge the significance of employing remedies for disease prevention, their motivation tends to be reactive rather than proactive. This finding is particularly applicable to our research group, which consists of individuals with an average age of nearly 60. The passive motivation and perceived health risk among this demographic can have a negative impact on their engagement in health information seeking. Therefore, it is important for e-Health providers and policymakers to implement comprehensive training programs aimed at enhancing consumers' health management capabilities and fostering active motivation, starting from an early age.

8. Conclusion

SOR has not been commonly applied in the health intervention technology research stream. Our study developed an integrated theoretical SOR framework research model to investigate e-Health service quality, satisfaction, and behavioral intentions. Our findings confirm that while e-Service quality is a universally applicable concept, its interpretation and implementation should be approached with a contextual understanding of the local culture and industry. Moreover, we propose the concept of "intention to act" as the ultimate outcome of satisfaction in stimulating users' responses regarding health-promoting activities. Our study supports the argument that patients' online experience influences their online and offline behavioral intentions. Patients' perception of the service quality of online consultation increases their satisfaction, which further promotes patients' intentions to consult online doctors and to use face-to-face consultations.

Finally, while the intention-behavior gap "requires more theoretical analysis to better understand this gap" (Shah and Zhingjun, 2021; Sheeran and Webb, 2016), several factors could act as moderators in bridging the gap between intention and behavior. It has been stated that "the use of e-health has accelerated dramatically during the coronavirus pandemic" (Wang et al., 2021). Thus, future research should further investigate which factors promote the intention to use e-Health services, the intention to act after using e-Health services and to turn these intentions into actual behaviors.

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References:

Akter, S., D'Ambra, J., & Ray, P. (2013). Development and validation of an instrument to measure user perceived service quality of mHealth. *Inf. Manag., 50*, 181-195.

Biduski, D., Bellei, E.A., Rodriguez, J.P., Zaina, L., & Marchi, A.C. (2020). Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire. *Comput. Hum. Behav., 104*, 106169.

Blut, M., Chong, A.Y., Tsigna, Z., & Venkatesh, V. (2022). Meta-Analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its Validity and Charting a Research Agenda in the Red Ocean. *J. Assoc. Inf. Syst., 23*, 10.

Blut, M., Chowdhry, N., Mittal, V., & Brock, C. (2015). E-Service Quality: A Meta-Analytic Review. *Journal of Retailing, 91, 4, pp.679-700.*

Bol, N., Smets, E., Rutgers, M., Burgers, J., Haes, H.D., Loos, E., & Weert, J.V. (2013). Do videos improve website satisfaction and recall of online cancer-related information in older lung cancer patients? *Patient education and counseling, 92 3*, 404-12.

Bol, N., Weert, J.V., Haes, H.D., Loos, E., Heer, S.D., Sikkel, D., & Smets, E. (2014). Using Cognitive and Affective Illustrations to Enhance Older Adults' Website Satisfaction and Recall of Online Cancer-Related Information. *Health Communication, 29*, 678 - 688.

Cao, Y., Li, J., Qin, X., & Hu, B. (2020). Examining the Effect of Overload on the MHealth Application Resistance Behavior of Elderly Users: An SOR Perspective. *International Journal of Environmental Research and Public Health, 17*.

Chang, S. H., Chih, W. H., Liou, D. K., & Hwang, L. R. (2014). The influence of web aesthetics on customers' PAD. *Computers in Human Behavior,* 36, 168–178.

Cho, N.H., Shaw, J., Karuranga, S., Huang, Y., Fernandes, J.D., Ohlrogge, A.W., & Malanda, B. (2018). IDF Diabetes Atlas: Global estimates of diabetes prevalence for 2017 and projections for 2045. *Diabetes research and clinical practice, 138*, 271-281.

Chobanian, A.V., Bakris, G.L., Black, H.R., Cushman, W.C., Green, L.A., Izzo Jr., J.L., Jones, D.W., Materson, B.J., Oparil, S., Wright Jr., J.T. and Roccella, E.J. (2003) 'The seventh report of the joint national committee on prevention, detection, evaluation, and treatment of high blood pressure: the JNC 7 report', *Journal of the American Medical Association*, Vol. 289, No. 19, pp.2560–2572.

Chopdar, P.K., & Balakrishnan, J. (2020). Consumers response towards mobile commerce applications: S-O-R approach. *Int. J. Inf. Manag., 53*, 102106.

Cohen J. E. (1988). Statistical Power Analysis for the Behavioral Sciences. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Crow, R.A., Gage, H., Hampson, S.E., Hart, J., Kimber, A., Storey, L., & Thomas, H. (2002). The measurement of satisfaction with healthcare: implications for practice from a systematic review of the literature. *Health technology assessment, 6 32*, 1-244.

Davis, F.D., Bagozzi, R.P., Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", Management Science, Vol. 35, No. 8, pp. 982-1003.

Deng, Z., & Liu, S. (2017). Understanding consumer health information-seeking behavior from the perspective of the risk perception attitude framework and social support in mobile social media websites. *International journal of medical informatics, 105*, 98-109.

Enwald, H.P.K., Niemelä, R.M., Keinänen-Kiukaanniemi, S., Leppäluoto, J., Jämsä, T., Herzig, K-H., Oinas-Kukkonen, H. and Huotari, M-L.A. (2012). Human information behaviour and physiological measurements as a basis to tailor health information. An explorative study in a physical activity intervention among prediabetic individuals in Northern Finland, *Health Information and Libraries Journal*, Vol. 29, No. 2, pp.131–140.

Finnish Diabetes Association (2021) *One out of Ten has Diabetes* [online] https://www.diabetes.fi/en/finnish_diabetes_association/diabetes_in_finland (accessed 21 September 2021).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 39-50.

Ghasemaghaei, M., & Hassanein, K. (2015). Online information quality and consumer satisfaction: The moderating roles of contextual factors - A meta-analysis. *Inf. Manag., 52*, 965-981.

Goyal, S., Chauhan, S., & Gupta, P. (2021). Users' response toward online doctor consultation platforms: SOR approach. *Management Decision*.

Hair, J.F., Risher, J.J., Sarstedt, M., & Ringle, C.M. (2019). When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev*., *31(1),* 2-24.

Hair J.F., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *Eur. Bus. Rev., 26(2)*, 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Henseler, J., Hubona, G.S. & Ray, P.A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Ind, Manag. Data Syst., 116(1),* 2-20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C.M. & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. of the Acad. Mark. Sci.,* 43**,** 115–135. https://doi.org/10.1007/s11747-014-0403-8

Heponiemi, T., Jormanainen, V., Leemann, L., Manderbacka, K., Aalto, A., & Hyppönen, H. (2020). Digital Divide in Perceived Benefits of Online Health Care and Social Welfare Services: National Cross-Sectional Survey Study. *Journal of Medical Internet Research, 22*.

Jamal, A., Khan, S.A., AlHumud, A., Al-Duhyyim, A., Alrashed, M., Shabr, F.B., Alteraif, A., Almuziri, A., Househ, M., & Qureshi, R. (2015). Association of Online Health Information–Seeking Behavior and Self-Care Activities Among Type 2 Diabetic Patients in Saudi Arabia. *Journal of Medical Internet Research, 17*.

Jarque, C. M. & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence residuals. *Economics Letters, 6*(3), 255-259.

Jung, T., Chung, N., & Leue, M. (2015). The determinants of recommendations to use augmented reality technologies: the case of a Korean theme park. *Tourism Management, 49*, 75-86.
Kahn, H., Cheng, Y.J., Thompson, T., Imperatore, G., & Gregg, E. (2009). Two Risk-Scoring Systems for Predicting Incident Diabetes Mellitus in U.S. Adults Age 45 to 64 Years. *Annals of Internal Medicine, 150*, 741-751.
Kauer, S.D., Mangan, C., Sanci, L. (2014). Do online mental health services improve help-seeking for young people? A systematic review. *Journal of Medical Internet Research* 16, e66.
Kennedy, P. E. (2003). A Guide to Econometrics, MIT Press, Cambridge, MA.
Kim, S., & Stoel, L. (2004). Apparel retailers: website quality dimensions and satisfaction. *Journal of Retailing and Consumer Services, 11*, 109-117.
King, R.A., Racherla, P., & Bush, V.D. (2014). What We Know and Don't Know about Online Word-of-Mouth: A Review and Synthesis of the Literature. *Journal of Interactive Marketing, 28*, 167 - 183.
Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, *11(4)*, 1-10.
Kock, N. (2020). *WarpPLS 7.0 User Manual*, Laredo, Texas: Scriptwarp Systems.
Koivumaki, T., Pekkarinen, S., Lappi, M., Vais€ anen,€ J., Juntunen, J., & Pikkarainen, M. (2017). Consumer adoption of future MyData-based preventive e-health services: An acceptance model and survey study. Journal of Medical Internet Research, 19(12), e429.
Kuske, S., Schiereck, T., Grobosch, S., Paduch, A., Droste, S., Halbach, S., & Icks, A. (2017). Diabetes-related information-seeking behaviour: a systematic review. *Systematic Reviews, 6*.
Kuske, H., Lee, Y., & Yoo, D. (2000). The determinants of perceived service quality and its relationship with satisfaction. *Journal of Services Marketing, 14*, 217-231.
Lanseng, E. J., & Andreassen, T. W. (2007). Electronic healthcare: A study of people's readiness and attitude toward performing self-diagnosis. International Journal of Service Industry Management, 18(4), 394–417.
Leung, L., & Chen, C.C. (2019). E-health/m-health adoption and lifestyle improvements: Exploring the roles of technology readiness, the expectation-confirmation model, and health-related information activities. *Telecommunications Policy*.
Mari, M., & Poggesi, S. (2013). Servicescape cues and customer behavior: a systematic literature review and research agenda. *The Service Industries Journal, 33*, 171 - 199.
Martin, S.F. (2017). Toward a Model of Word-of-Mouth in the Health Care Sector. *Journal of Nonprofit & Public Sector Marketing, 29*, 434 - 449.
Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology.* Cambridge, MA: MIT Press.
Nabi, R.L., Huskey, R., Nicholls, S.B., Keblusek, L., & Reed, M.E. (2019). When audiences become advocates: Self-induced behavior change through health message posting in social media. *Comput. Hum. Behav., 99*, 260-267.
National Diabetes Statistics Report 2020: Estimates of Diabetes and its Burden in the United States. Centers for Disease Control Prevention. URL: https://www.cdc.gov/diabetes/pdfs/data/statistics/national-diabetes-statistics-report.Pdf [last accessed 06 September 2021].
Nunnally, J. C. (1978). *Psychometric Theory* (2nd ed.), McGraw-Hill, New York NY.

Or, C., & Karsh, B. (2009). Review Paper: A Systematic Review of Patient Acceptance of Consumer Health Information Technology. *Journal of the American Medical Informatics Association: JAMIA, 16 4*, 550-60.

Parasuraman, A., Zeithaml, V. and Berry, L.L. (1988), "SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality", *Journal of Retailing*, Vol. 64, Spring, pp. 12-40

Parasuraman, A., Zeithaml, V. and Berry, L.L. (1991), "Refinement and reassessment of the SERVQUAL scale", *Journal of Retailing*, Vol. 67 No. 4, pp. 420-50

Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). ES-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, **7**(3), 213-233.

Parboteeah, D. V., Valacich, J. S., & Wells, J. D. (2009). The influence of website characteristics on a consumer's urge to buy impulsively. *Information Systems Research, 20*(1), 60–78.

Pauli, G., Martin, S.F., & Greiling, D. (2022). The current state of research of word-of-mouth in the health care sector. *International Review on Public and Nonprofit Marketing, 20*, 125-148.

Pekkaya, M., Pulat İmamoğlu, Ö., & Koca, H. (2019). Evaluation of healthcare service quality via Servqual scale: An application on a hospital. *International Journal of Healthcare Management, 12*, 340 - 347.

Preaux, J., Casadesus, M., & Bernardo, M. (2022). A Conceptual Model to Evaluate Service Quality of Direct-to-Consumer Telemedicine Consultation from Patient Perspective. *Telemedicine journal and e-health: the official journal of the American Telemedicine Association*.

Rodriguez, P.G., Villarreal, R., Valiño, P.C., & Blozis, S.A. (2020). A PLS-SEM approach to understanding E-SQ, E-Satisfaction and E-Loyalty for fashion E-Retailers in Spain. *Journal of Retailing and Consumer Services, 57*, 102201.

Sawesi, S.A., Rashrash, M., Phalakornkule, K., Carpenter, J.S., & Jones, J.F. (2016). The Impact of Information Technology on Patient Engagement and Health Behavior Change: A Systematic Review of the Literature. *JMIR Medical Informatics, 4*.

Shah, S.K., & Zhongjun, T. (2021). Elaborating on the consumer's intention–behavior gap regarding 5G technology: The moderating role of the product market-creation ability. *Technology in Society*.

Sheeran, P., & Webb, T.L. (2016). The Intention–Behavior Gap. *Social and Personality Psychology Compass, 10*, 503-518.

Shen, C., Wang, M., Wan, A., Viswanath, K., Chan, S., & Lam, T. (2018). Health information exposure from information and communication technologies and its associations with health behaviors: Population-based survey. *Preventive medicine, 113*, 140-146.

Stone, J., & Fernandez, N. (2008). To practice what we preach: The use of hypocrisy and cognitive dissonance to motivate behavior change. *Soc. Personal. Psychol. Compass,* 2(2), 1024 –1051.

Sheon, A.R., Bolen, S.D., Callahan, B., Shick, S., & Perzynski, A.T. (2017). Addressing Disparities in Diabetes Management Through Novel Approaches to Encourage Technology Adoption and Use. *JMIR Diabetes, 2*.

Schwarz, A., Rizzuto, T., Carraher-Wolverton, C., Roldan, J., & Barrera-Barrera, R. (2017). Examining the impact and detection of the "Urban Legend" of Common Method Bias. *Data Base Adv. Inf. Syst., 48(1)*, 93-119.

Tao, D., Wang, T., Wang, T., Zhang, T., Zhang, X., & Qu, X. (2020). A systematic review and meta-analysis of user acceptance of consumer-oriented health information technologies. *Comput. Hum. Behav., 104*, 106147.

Valkenburg, P. M. (2017). Understanding self-effects in social media. *Human Communication Research*, 43(4), 477 –490.

Verkijika, S.F., & Wet, L.D. (2019). Understanding word-of-mouth (WOM) intentions of mobile app users: The role of simplicity and emotions during the first interaction. *Telematics Informatics, 41*, 218-228.

Verma, P., Kumar, S., & Sharma, S. (2020). e-Healthcare service quality: consumer satisfaction and its association with demographic characteristics. *International journal of health care quality assurance,* Vol 3 (6), pp. 413-428.

Verma, P., Kumar, S., & Sharma, S.K. (2021). Evaluating the total quality and its role in measuring consumer satisfaction with e-healthcare services using the 5Qs model: a structure equation modeling approach. *Benchmarking: An International Journal*.

Wang, W., Sun, L., Liu, T., & Lai, T. (2021). The use of E-health during the COVID-19 pandemic: a case study in China's Hubei province. *Health Sociology Review, 31*, 215 - 231.

Weert, J., Munster, B., Sanders, R., Spijker, R., Hooft, L., & Jansen, J. (2016). Decision aids to help older people make health decisions: a systematic review and meta-analysis. *BMC Medical Informatics and Decision Making, 16*.

Yang, H., Guo, X., & Wu, T. (2015). Exploring the influence of the online physician service delivery process on patient satisfaction. *Decis. Support Syst., 78*, 113-121.

Zhang, Y., & Li, X. (2017). Uses of information and communication technologies in HIV self-management: A systematic review of global literature. *International Journal of Information Management, 37*(2), 75–83.

Zeithaml, V., Berry, L.L., & Parasuraman, A. (1993). The nature and determinants of customer expectations of service. *Journal of the Academy of Marketing Science, 21*, 1-12.

Zeithaml, V.A., A. Parasuraman, Malhotra, A. (2002). Service quality delivery through websites: a critical review of extant knowledge, *Journal of the Academy of Marketing Science* 30 (4), 362–375.

Appendix 1: Explanation of the components of our service quality model in comparison with other service quality models (detailed with definitions)

Components of our service quality model, incl. definitions	SQ Model of Telemedicine Service (Preaux et al., 2022)	E-Service quality (Blut et al., 2015)	E-S-QUAL (Parasuraman et al., 2005)	Traditional SQ (SERVQUAL) (Parasuraman et al., 1988)
Information Quality: Informational fit-to-task, providing adequate information to support a customer's task.	**Information usefulness *(in use quality)*** "measures the patient's perceived quality of information received during the remote consultation" (Page 14)	**Information Quality** (*in Website design*)**:** Consumer's experience on the Website, specifically Website information quality.	**Efficiency 4 (EFF4):** Information at this site is well organized (***in Efficiency***)	No
Attraction (Visual Appeal): Represent visual quality of a website. Relates to the choice of fonts and other visual elements such as graphics, acts to enhance the overall look of a website.	**Website design *(in system quality)*:** "describes the degree to which the DTC telemedicine platform is easy to use and aesthetic owing to its clear layout and visually pleasing design." (Page 12)	No	No	**Tangibles** (Visually appealing facilities and visually appealing material associated with services): Physical facilities, equipment, and appearance of personnel.
Emotional support: involves the articulation of emotional concerns, encompassing qualities such as care, understanding, empathy, trust and love	**Empathy *(in interaction quality)*:** "reflects the patient's perception of the doctor focusing on his best interest and showing personal attention." (Page 12)	No	No	**Empathy:** Caring, individualized attention the firm provides its customers.
Perceived Ease of Use: Refers to the degree to which the prospective user expects the target system to be free of effort.	**Ease of Use (*in use quality*):** "is defined as the patient's perceived convenience while applying for the teleconsultation…" (Page 13)	**Website convenience** (*in website design*)**:** Consumer's experience on the Website, specifically Website convenience/ease of use.	**Efficiency 1 (EFF1)**: This site makes it easy to find what I need; **EFF2:** It makes it easy to get anywhere on the site; **EFF6:** This site is simple to use (*in Efficiency)*	No

Appendix 2: Items and variables

Variables	Items	Sources
Visual appeal (ATR)		Bol et al., 2013; Kim & Stoel, 2004; Parboteeah et al., 2009
ATR1	The diabetes risk assessment is well-organized	
ATR2	The diabetes risk assessment displays visually pleasing design	
ATR3	The display pages of diabetes risk assessment is easy to read	
ATR4	The diabetes risk assessment is visually appealing	
ATR5	The diabetes risk assessment is creatively realized	
Information Quality (INQ)		Kim & Stoel, 2004
INQ1	I can interact with the diabetes risk assessment in order to get information tailored to my specific needs	
INQ2	The diabetes risk assessment has interactive features, which help me accomplish my task	
INQ3	The diabetes risk assessment allows me to interact with it to receive tailored information	
INQ4	The diabetes risk assessment adequately meets my information needs	
Perceived Ease of Use (PEOU)		Davis et al., 1989
PEOU1	I find the service to be easy to use	
PEOU2	Using the service does not require a lot of my mental effort	
PEOU3	I find the information and language of the services are clear and understandable	
PEOU4	I find learning how to use the service is not too difficult	
Emotional Support (EMS)		Bol et al.2013
EMS1	The services help me to deal with stress	
EMS2	The services help with my emotions	
EMS3	The services increase my self-confidence	
EMS4	The services give me ease of mind	
Satisfaction (SAT)		Bol et al.2013; Kim & Stoel, 2004
SAT1	Taking the test at this website was a satisfying experience	
SAT2	All things considered, I find using the diabetes risk assessment to be a wise thing to do	
SAT3	All things considered, I find using the diabetes risk assessment to be a good idea	
SAT4	All things considered, I find using the diabetes risk assessment to be a positive thing	
Word of Mouth (WOM)		Hamari & Koivisto, 2015
WOM1	I would recommend the diabetes risk assessment to my friends and family if I know they are concerned about these problems	
WOM2	I would recommend the diabetes risk assessment to anyone who seeks my advice	
WOM3	I will refer my acquaintances to the diabetes risk assessment	

WOM4	I will say positive things about the diabetes risk assessment to other people	
Intention to use (ITU)		Davis et al., 1989
ITU1	I will use the diabetes risk assessment when I have a need for it again	
ITU2	I intend to use the diabetes risk assessment at least as often as I have previously used	
ITU3	I intend to use the diabetes risk assessment more frequently than I have previously used	
ITU4	Assuming I continue using the diabetes risk assessment, I intend to use the service provided by the current provider	
ITU5	Given that people are informed about the diabetes risk assessment, I predict that more people would use it	
Intention to act (ITA)		Self-developed
ITA1	Check further information for different sources	
ITA3	Make an appointment to see a specialist	
ITA4	I plan to increase the number of physical activities	
ITA6	I plan to change my diet behavior	

Feedback to Reviewer:

We thank you for your comments which helped us to improve the paper. Please see below how we have addressed your comments. Your comments are given on regular type and our responses are provided on bold type, under the comments that they relate to.

I cannot locate certain cited papers such as the SQ Model of Telemedicine Service (Preaux & Bernardo, 2020), Blut et al., 2015 etc.

Thank you for pointing this out. We found that we had made a mistake regarding Preaux & Bernardo (2020); in fact, this source is Preaux et al. (2022). We corrected this mistake.

Regarding Blut et al. (2015), we found that the source was missing from the reference list, and we added it there.

Table 1 does not make much sense. The authors should add a first row and column that explain what each cell is referring to. From Table 1, it also appears that the authors are stating that “use quality” is equivalent to “perceived eou” and “information quality”. From Table 1, it also appears that the authors are stating that “efficiency” is equivalent to “perceived eou” and “information quality”. From Table 1, are the authors declaring that “efficiency” is that same as “information quality”? From table 1, why if the extant literature employees “empathy” did the authors change the construct to “emotional support” ? Therefore, there is still no adequate explanation of why the particular stimulus constructs were selected. The authors should clearly demonstrate how they selected to employ these particular stimulus constructs.

Thank you for this suggestion. Due to word limitations, our initial explanation lacked detail, potentially leading to confusion, as highlighted in your review. We have decided to make revisions, focusing on Table 1 and the text referring to it. The table provides an explanation of the components of our service quality model and its components, including a comparison to other service quality models. We made this point now clearer in the explanation referring to the Table, the Table title, as well as in the left-hand corner cell.

Similar to pointed out by the reviewer, we also recognize that readers might wonder why and how the components relate to other models, as constructs have different names. To clarify the definitions of our service quality components and how they relate to other models, we have included an Appendix Table (Appendix 1) that offers a detailed explanation. We hope that this Appendix Table will convince readers that the sources we have drawn inspiration from are similar to our service quality components, despite sometimes having different construct names. We explain more herein.

In the model of Preaux et al. (2022), the "use quality" construct (first-order construct) encompasses information usefulness and ease of use as second-order constructs. To enhance clarity, we refrain from explicitly mentioning "use quality" in the revised Table 1. However, in Appendix 1, we provide a comprehensive explanation, explicitly including the concept of use quality.

Similarly, in the model of Parasuraman et al. (2005), the "efficiency" construct combines information quality and perceived ease of use. Both in the revised Table 1 and Appendix 1, we specify which items within this construct are related to information quality and perceived ease of use.

Rather than using the term "empathy," we opt for the term "emotional support." There is no intention to mislead readers by the use of this name and we understand that the name "empathy" could be used as well for the construct. Emotional support is defined as the provision of warmth and nurturance, encompassing encouragement, empathy, and sympathy (Deng and Liu, 2017). We believe that the term "emotional support" is more inclusive and user-friendly than "empathy." It is also more accurate that a website may act as a medium to convey an organization's or a doctor's empathy, rather than feeling empathy by itself. Moreover, in the healthcare context, this term aligns with terminology used in related research. Examples of other healthcare research papers employing the term "emotional support" are provided below:

Zhang, X., Liu, S., Chen, X., Wang, L., Gao, B., & Zhu, Q. (2017). Health information privacy concerns, antecedents, and information disclosure intention in online health communities. *Inf. Manag., 55*, 482-493.

Deng, Z., & Liu, S. (2017). Understanding consumer health information-seeking behavior from the perspective of the risk perception attitude framework and social support in mobile social media websites. *International journal of medical informatics, 105*, 98-109 .

Jin, J., Yan, X., Li, Y., & Li, Y. (2016). How users adopt healthcare information: An empirical study of an online Q&A community. *International journal of medical informatics, 86*, 91-103 .