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Antecedents of Perceived Usefulness (PU) and Perceived Ease-of-Use (PEOU) in the Heuristic-Systematic Model: The Context of Online Diabetes Risk Test

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Abstract

E-Health services are seen as promising to healthcare promotion, but low usage by patients limits their effectiveness. The Technology Acceptance Model (TAM) has shown to be explanatory in the adoption of e-Health services. As the use of e-Health for self-management grows, it is important to identify factors influencing perceived ease-of-use (PEOU) and usefulness (PU) to encourage acceptance. However, the selection of external variables in this context lacks a clear pattern. We applied the Heuristic-Systematic Model (HSM) with the aim of further explaining the external variables in TAM especially in the area of e-health, and selected three external variables: information quality, health information literacy, and social influence. Hence, our study combines the Heuristic-Systematic Model (HSM) and TAM to investigate the mechanism and external factors that promote individuals to act for their health benefits. A total of 198 responses were collected among people having completed an online diabetes risk test on the website of the Finnish Diabetes Association. This data was then analyzed using partial least squares structural equation modeling (PLS-SEM). Our study finds that heuristic cues like health information literacy and social influences impact PEOU, while systematic cues, especially information quality, positively influence PU. Also, higher PU is associated with increased intention to use e-Health services and engage in health-promoting actions, highlighting the importance of the systematic path in the e-Health context. Our theoretical contributions are twofold. First, we add to TAM research in the area of e-health by providing an explanation why heuristic cues link to PEOU while systematic cues link to PU. Second, our research is among very few applying HSM to e-health and finds that overall, the systematic path is more influential than the heuristic path. We also provide practical advice for healthcare providers to improve the impact of their e-health initiatives.

Keywords : E-Health, Health Self-management, Diabetes, Online Risk Test, Heuristic-systematic Model, Technology Acceptance Model, Health Literacy, Social Influence, Information Quality

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1. Introduction

E-Health is defined as "the organization, delivery and consumption of health services and information via the Internet and related technologies" [Jiang et al., 2015]. The use of the Internet for health information is becoming increasingly popular and citizens are also following through with health-related actions based upon such information [Xiao et al., 2014]. Thus, increased use of eHealth, and particularly Web-based information for health-related actions, has emerged as a viable route to provide healthcare services that are accessible and cost-effective for citizens. Understandably, the most common interests for people in searching health information have found to be symptoms, conditions, and treatment options [Shuyler and Knight, 2003]. Health self-management applications and Websites that allow individuals to obtain health information preventing future disease or even enabling self-diagnosis is a promising approach [Lanseng and Andreassen, 2007; Koivumaki et al., 2017], but one which requires the active participation of the public, shifting attention to eHealth adoption conditions.

The Technology Acceptance Model (TAM) has been found to have good explanatory power in the adoption of e-Health services [Holden and Karsh, 2010; Tao et al., 2020; Chauhan and Jaiswal, 2017]. TAM originated from research conducted by Davis et al. [1989]. It adapted the Theory of Reasoned Action (TRA) to the context of work-related technology acceptance. TAM primarily consists of two key variables: perceived ease-of-use (PEOU) and perceived usefulness (PU). PEOU reflects the level of effort required to use the technology, while PU indicates the extent to which technology use enhances one's performance [Davis, 1989]. Given the importance of the antecedents of PEOU and PU, often referred to as "external factors" [Davis et al., 1989, p. 985; Abdullah et al., 2016; Benbasat and Barki, 2007; Chuttur, 2009], it is crucial to focus on them. External variables provide a better understanding of the factors influencing PU and PEOU, and their presence guides the actions necessary to foster increased technology use [Legris et al., 2003].

Many authors have incorporated numerous potential external factors in their studies, aiming to enhance the predictive validity of TAM and its variables, namely PEOU and PU. For instance, Yousafzai et al. [2007] found that researchers have proposed over 70 external variables influencing PU and PEOU. These external variables can be categorized into four main categories: organizational, system-related, users' personal characteristics, and other variables [Yousafzai et al., 2007a]. However, the review by Legris et al. [2003] noted that there is no clear pattern regarding the selection of external variables considered. A review conducted by Al-Emran et al. [2018] revealed that approximately 22% of the reviewed articles extended the TAM model by incorporating factors primarily derived from prominent Information Systems (IS) theories such as the DeLone and McLean information system success model and the Expectation-confirmation model. Dual-process theories, though confirmed by Bhattacherjee and Sanford [2006] to be a referent theory for TAM, have been less applied. However, dual-process theories have been recently used heavily in relation to online information [Lee and Lin, 2022; Zhang et al., 2023], an area that has similarities with health self-management. Therefore, with this study, we wish to apply one of the dual-process theories, the Heuristic-Systematic Model (HSM).

The Heuristic-Systematic Model (HSM) focuses on explaining attitude formation through information about the world by two main processing routes, systematic and heuristic [Chaiken, 1980; Chaiken and Ledgerwood, 2012; Davis and Tuttle, 2013; Shi et al., 2020; Zhang et al., 2014]. Although HSM has been applied to various technology adoption contexts [Davis and Tuttle, 2013; Zhang et al., 2014; Shi et al., 2020], its application in e-Health services has been limited. Considering these points, in this study, we aim to integrate HSM into TAM to investigate the external factors influencing e-Health service acceptance. By utilizing an integrated research model based on HSM and TAM, we seek to gain insights into the influential factors that shape attitudes and promote the acceptance of e-Health services, ultimately contributing to effective health self-management. Our selection of external variables is based on the study context, related to health self-management, but also the selection of representative external variables for both processing routes in HSM. We selected an online diabetes risk test as a case study for this research since for diabetes, the use of technological tools is critical to foster health self-management [Adu et al., 2019].

This paper is organized as follows. First, we present the literature review and the variables and hypotheses used in the paper (section 2). Second, we explain our research method and the sample collection (section 3). Third, we present the results of the analysis (section 4) and discuss these results (section 5). Finally, we conclude with theoretical and practical implications of the results, the limitations of the research, and future research directions (sections 6 and 7).

2. Literature Review and Hypothesis Development

2.1 Heuristic-Systematic Model (HSM)

When people use an online diabetes risk test, they will answer the questions on a website/app and receive a result which evaluates their risk level of developing diabetes in the next ten years. Then, they may expend effort to scrutinize this information and judge whether it is correct and valuable for them. This information processing route corresponds to the systematic path in HSM. On the other hand, some users may not make such efforts to scrutinize the health information; instead, they use their subjective knowledge and information from their social circles, which they can easily obtain and use as an additional explanation. This second information processing route corresponds to the heuristic path.

In our research, information quality is a cue for systematic information processing. This builds from the research of Zhang et al. [2014] and James et al. [2021], who linked the variables argument quality and information sufficiency to systematic processing under the HSM model. However, numerous studies have applied information quality [Yang et al., 2006; Chen et al., 2018], argument quality [Bhattacherjee and Sanford, 2006], and similar variables [Iranmanesh et al., 2024] in the same role under an aligned dual-process theory [Eagly and Chaiken, 1993; Angst and Agarwal, 2009], the Elaboration-Likelihood Model. Since individuals deeply scrutinizing information and the arguments within it, and deliberating on this information at length would be likely to concern themselves with information quality, we determine that the variable should be a cue for systematic processing.

On the other hand, we use the antecedent variables subjective health information literacy and social influence as cues for heuristic information processing. Regarding health information literacy, James et al. [2021] used information gathering capacity as a heuristic cue in the HSM model, and Bhattacherjee and Sanford [2006] used user expertise in the same role under the ELM model. This suggests to us that context-relevant ability, including health information literacy, should be treated as a heuristic cue. Having that ability, individuals feel like they are able to skip deep deliberation and consideration in the information processing, resulting in the heuristic approach.

Regarding social influence, Zhang et al. [2014] and James et al. [2021] linked the variables source credibility and subjective norm to heuristic processing under the HSM model. Other studies have applied similar variables, namely, social norm [Bhattacherjee and Sanford, 2006], reputation [Chen et al., 2018] and electronic word-of-mouth [Cao et al., 2017], to serve this purpose in the ELM model. Social influence, norms, and reputation are factors that enable individuals to come to quick judgements in information processing. Instead of detailed consideration of arguments, they can form beliefs based on what they know about associates' opinions or the majority view, which suggests to us that social influence should be a heuristic cue. Next, we build the hypotheses involving HSM and external variables of TAM.

2.1.1 Information Quality (INQ) in Systematic Processing

INQ is essential for information systems and the Internet because these technologies mainly process and present information, and decisions that are made depend on the characteristics of the information [Singh and Singh, 2018]. INQ is connected to the usefulness of technology and the ease-of-use of a technology [Ghasemaghaei and Hassanein, 2015]. Especially, in e-Health services, patients' ability of selecting, accepting and using e-Health services is strengthened by INQ characteristics including accuracy, completeness, relevance, and reliability [Plotnikoff et al., 2017]. In other words, e-Health INQ helps users find the usability and utility of e-Health services which will support them in managing their health condition [Pai and Huang, 2011]. Hence, we hypothesize that:

H1a: INQ will positively affect PEOU.
H1b: INQ will positively affect PU.

2.1.2 Subjective Health Information Literacy (HIL) in Heuristic Cues

Subjective HIL refers to individuals' self-perceived knowledge and understanding of health-related information to make good health-related decisions [Berkman et al., 2010]. However, according to Schulz et al. [2021], the perception of HIL has been increasingly measured subjectively via self-reports. Thus, in our study, we considered self-reported HIL as the subjective knowledge of e-Health services users. While subjective knowledge allows e-Health service users to form overall conclusions about the topic of concern, it lacks detailed information and ability to evaluate new information in a rational and logical manner. This makes e-Health users more vulnerable to making judgments based on simplified assessments of information related to the topic. In other words, e-Health service users apply subjective HIL as heuristic cues in processing this information.

Moreover, users with higher subjective HIL may perceive e-Health services to be easier to navigate and comprehend. Their confidence in understanding health-related content empowers them to interact with the service more effortlessly, leading to a perception of enhanced ease-of-use. There have been published studies finding that the ease-of-use and usefulness of health information technology apps are linked to HIL [Mackert et al., 2016]. Similarly, Wu et al. [2007] and Abdullah et al. [2016] found that self-efficacy had significant positive relationships with PU and PEOU in m-Healthcare and e-portfolios. Thus, we can expect the link between subjective HIL and PEOU and PU as hypothesized below.

H2a: Subjective HIL will positively affect PEOU.
H2b: Subjective HIL will positively affect PU.

2.1.3 Social Influence (SOI) in Heuristic cues

According to Venkatesh et al. [2003], SOI refers to the degree of perceived importance of other persons' opinions to one's own decisions regarding the use of technology. It assumes various sources of information about other people's opinions, such as personal contacts and the mass media [Wei et al., 2009]. SOI has been recognized as a significant heuristic cue in online shopping and AI recommendation system in travel planning, impacting customers' favorable attitudes toward product evaluations [Cheung et al., 2014; Shi et al., 2020]. SOI has been found to influence users' perceptions regarding the usefulness and usability of information systems. It is also a factor in the ease-of-use and usefulness of health technologies [Sun and Rau, 2015]. Thus, this research hypothesizes that:

H3a: SOI will positively affect PEOU.
H3b: SOI will positively affect PU.

2.2 Technology Acceptance Model (TAM)

2.2.1 Perceived Ease of Use (PEOU)

PEOU means how easy or effort-free it is for a person to use a technology [Davis, 1989]. Previous studies found that PEOU can strengthen PU [Venkatesh et al., 2003; Tao et al., 2020] and the intention to use (ITU) [Tao et al., 2020]. In the e-Health context, persuasive technologies, or health self-management, scholars found that PEOU affected PU and ITU of services positively [Beldag and Hegner, 2017; Guo et al., 2013; Xue et al., 2012]. Moreover, ease-of-use or usability of e-Health services can make one interested and excited about connected health activities. Thus, e-Health services enable users to carry out more healthy activities if they are easy to test. Thus, the following hypotheses are proposed.

H4a: PEOU will positively affect PU.
H4b: PEOU will positively affect ITU.
H4c: PEOU will positively affect ITA.

2.2.2 Perceived usefulness (PU)

In the e-Health context, persuasive technologies or health self-management, the relationship between PU and intentions has been found in previous studies such as Chauhan and Jaiswal [2017], Guo et al. [2013]; Tao et al. [2020]; and Xue et al. [2012]. In addition, the usefulness of e-Health services could influence people's activities such as checking and preventing health risk behaviors [Bigsby and Hovick, 2018], seeking help, increasing self-care for diabetes patients [Jamal et al., 2015], and engaging with doctors [Barello et al., 2016]. Essentially, e-Health services enable users to carry out more healthy activities if they can show their usefulness for the users. Thus, this research sets the following hypotheses.

H5a: PU will positively affect ITU.
H5b: PU will positively affect ITA.

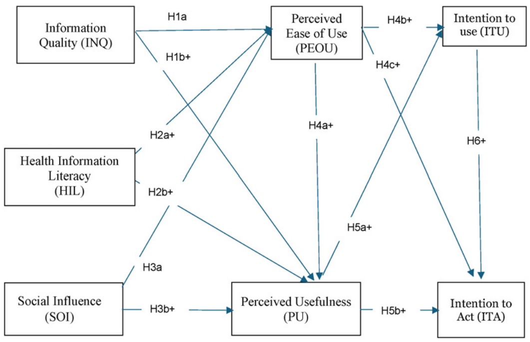
2.2.3 Intention to Use (ITU) and Intention to Act (ITA)

TAM [Davis et al., 1989] focuses on the dependent variable of use intention, which can be applied to an individual's interest in accepting technologies in various usage areas, including e-health [Hepola et al., 2020; Tao et al., 2020]. An individual may first benefit from a technology when they adopt and start using it, for example, an e-health service [Leung and Chen, 2019], making use intentions very important. More importantly, these health technologies can foster health-oriented behaviors, sometimes called "self-health management" behaviors. We call this effect "intention to act." (ITA) Although ITA is the ultimate goal for such technologies, ITU comes first. Previous studies have investigated the link between the use of online services and the subsequent impact on users' daily activities. For example, Hamari and Koivisto [2015] describe an online game, Fitocracy, that encouraged users to exercise. This exercise would be an example of ITA. In addition, most of the participants (93%) in the survey of Jamal et al. [2015] reported that after searching online health information regarding the self-care activities of Type 2 Diabetic Patients, they positively change their behaviors to aim for better health condition. Therefore, we define the hypothesis:

H6: ITU will positively affect ITA.

2.3 Research Model

In summary, we propose an integrated model based on HSM and TAM to predict the behaviors of e-Health users, as depicted in ⟨Figure 1⟩.



⟨Figure 1⟩ Research Model

⟨Figure 1⟩ presents the research model which depicts the eight latent constructs embedded in a hypothesized, directional nomological network.

3. Research Method

3.1 Development of Measurement Tools

This research is based on a survey focused on respondents' experiences regarding an online diabetes risk test implemented in Finland. In addition to the context of the risk test, the questionnaire also queried users on their health-related behavioral intention following the test and certain background information. The languages available for the questionnaire were Finnish and Swedish (the two national languages of Finland) and English. Most of the constructs apart from two variables (i.e., ITA and HIL) were adapted from previous studies to fit the study context (see 〈Appendix〉). All items were measured with Likert scales of five points (from 1 = totally disagree to 5 = totally agree).

As there was no previous research having the ITA construct, which indicates health-directed behaviors towards diabetes risk management, we developed it based on reviewing the previous diabetes studies. According to the report of National Diabetes (U.S), 2020, diabetes risk factors such as overweight or obese (BMI of 25.0 kg/m^2 or over), unhealthy diet, and physical inactivity, can be modifiable to reduce the risk level. Supporting this argument, Kuske et al. [2017] also found that information about "diet," "complications," "exercise," and "medications" were the most frequently searched by Internet users. Thus, we built the construct of ITA to include the five items as listed in the appendix.

The HIL instrument was built according to the findings of Niemelä et al. [2012]. Their factor analysis suggests a three-factor structure (awareness, access, and assessment) in which awareness and assessment appear the most consistent across populations [Hirvonen et al., 2020]. Focusing on the most consistent measures, the present study settled on a scale measuring HIL through the stable dimensions using the three items, which measure awareness and assessment (see the 〈Appendix〉).

The instrument was pre-tested on four subjects with experience with e-health services. This resulted in a revised version with the new inclusions of respondent background, user experience, and behavior. The Appendix shows the final version of the instrument.

3.2 Sample Collection

The data was collected online via Webropol (www.webropolsurveys.com) and accessed from the website of the Association. Before starting the survey, we provided appropriate informed consent to the participant in which we clearly stated that the collected data will be managed confidentially and are used only for research purposes. The responses will not contain any personal information and will be held anonymous in the analysis and reporting of the data.

Qualified respondents to the survey were those who had first completed the diabetes risk test on the website of the Finnish Diabetes Association (https://www.diabetes.fi/riskitesti), which is popular for searching diabetes-related information in Finland. The risk test and associated survey were further advertised through social media and a university press release. It was started in November 2017 and kept active for ten months.

Today, self-health management continues to be a topical research area in relation to several diseases including diabetes [te Braake et al., 2024; Schmidt et al., 2022; Vollrath et al., 2024]. While arguably a gradual trend in Website use over smartphones and tablets, rather than personal computers, is observable since 2017-18, the Websites themselves have not changed very much; underlining that variables such as INQ and SOI would be unaltered for investigations in the current time period. This is demonstrated by the same factors and theories being investigated for mobile health

〈Table 1〉 Demographic Profile of Respondents

Classification		Number of Participants	Percentage (%)
Gender	Male	64	32.32
	Female	134	67.68
Age	Below 45 years old	39	19.7
	45-54 years old	20	10.1
	55-64 years old	44	22.2
	Over 64	95	48.0
Education	Basic education	38	19.2
	Upper secondary or vocational school	55	27.8
	Bachelor Degree	54	27.3
	Postgraduate Degree	48	24.2
	Others	3	1.5

[Harakeh et al., 2022; Sze and Kow, 2023; van Elburg et al., 2023]. Therefore, we believe that our data will continue to show relevant patterns and insights despite its collection period being a few years in the past.

Our resulting sample size was 198 (with six incomplete answers eliminated from the total number of 204 responses). The descriptive variables are shown in 〈Table 1〉. It is conspicuous that women comprise most of the sample (68%). This can be explained by the fact that women generally seek health information more than men [Torrent-Sellens et al., 2016] and tend to use online tests more than men. The sample is also weighted toward older users, the mean respondent age being 58.64 years old. This is also understandable since Type 2 diabetes (the focus of this study) increases in incidence after the age of 45 years old [Heikes et al., 2008]. Indeed, 80% of our sample comprises people at least 45 years old. More than half of the respondents possessed a university degree.

4. Data analysis and Results

We chose the partial least squares structural equation modeling (PLS-SEM) technique to analyze our model using SmartPLS 4.0.7.8 [Ringle et al., 2022]. We chose this technique since it “provides more accurate estimates with small sample sizes, […] is more appropriate when models are complex [… and] when prediction is a primary focus of the research [Hair et al., 2020, p. 108].

4.1 Measurement (outer) Model

We followed the steps of Hair et al. [2020] to confirm the measurement model quality that are relevant to our context: 1) estimate loadings and significance, 2) indicator reliability, 3) composite reliability, 4) average variance extracted (AVE), and 5) discriminant validity.

First, we ran bootstrapping (5000 subsamples). We checked the t-statistics of the item loadings for significance. We dropped the items that loaded below the threshold of 0.7 [Hair et al., 2020]. Thus, we removed INQ4, ITA2, and ITA3 (see the 〈Appendix〉) before we proceeded with the data analysis. Second, the constructs items loadings were squared to show that every item shared acceptable variance with its corresponding construct. Third, after establishing indicator reliability, we established internal composite reliability (ICR) of all the model constructs by meeting the threshold of 0.70 for ICR. Fourth, we established convergent validity of all the model constructs by meeting the threshold of 0.5 for the average variance extracted (AVE). These results are shown in ⟨Table 2⟩.

For Step 5, to measure the constructs' distinctiveness, we verified that the square root of the average variance extracted (bolded diagonal) is higher than the correlation of the construct with any other construct in our model (off-diagonal) [Fornell and Larcker, 1981], as shown in ⟨Table 3⟩.

In addition, we confirmed the discriminant validity of our measures by using the hetero-

⟨Table 2⟩ ICRs, AVEs, and Loadings

	Item	HIL	INQ	ITA	ITU	PEOU	PU	SOI
	ICR	0.82	0.86	0.83	0.88	0.94	0.90	0.95
	AVE	0.60	0.61	0.50	0.59	0.80	0.65	0.83
(1)	HIL1	**0.73**	0.04	0.34	0.38	0.26	0.22	-0.03
	HIL2	**0.75**	0.07	0.22	0.11	0.24	0.17	-0.18
	HIL3	**0.83**	0.18	0.32	0.31	0.27	0.30	-0.18
(2)	INQ1	0.16	**0.85**	0.29	0.48	0.06	0.45	0.11
	INQ2	0.08	**0.82**	0.27	0.39	-0.09	0.36	0.26
	INQ3	0.07	**0.87**	0.23	0.32	-0.10	0.31	0.11
(3)	ITA1	0.38	0.26	**0.74**	0.40	0.20	0.32	-0.13
	ITA4	0.29	0.21	**0.84**	0.36	0.27	0.38	-0.08
	ITA5	0.23	0.26	**0.76**	0.30	0.20	0.32	0.06
(4)	ITU1	0.26	0.45	0.32	**0.80**	0.20	0.47	-0.04
	ITU2	0.31	0.43	0.30	**0.82**	0.13	0.50	0.20
	ITU3	0.17	0.38	0.33	**0.75**	0.04	0.48	0.31
	ITU4	0.30	0.30	0.40	**0.76**	0.31	0.35	0.06
	ITU5	0.36	0.28	0.44	**0.73**	0.30	0.33	-0.05
(5)	PEOU1	0.31	-0.02	0.18	0.19	**0.90**	0.39	-0.24
	PEOU2	0.32	-0.03	0.29	0.24	**0.95**	0.42	-0.25
	PEOU3	0.23	-0.03	0.34	0.22	**0.85**	0.38	-0.19
	PEOU4	0.32	-0.09	0.21	0.24	**0.87**	0.30	-0.31
(6)	PU1	0.33	0.27	0.32	0.43	0.46	**0.83**	-0.01
	PU2	0.24	0.42	0.42	0.40	0.17	**0.82**	0.13
	PU3	0.27	0.41	0.41	0.54	0.34	**0.88**	0.01
	PU4	0.26	0.30	0.34	0.45	0.59	**0.76**	-0.12
	PU5	0.09	0.44	0.24	0.38	0.00	**0.72**	0.26
(7)	SOI1	-0.15	0.12	-0.10	0.09	-0.30	0.01	**0.92**
	SOI2	-0.23	0.16	-0.12	0.08	-0.30	0.02	**0.96**
	SOI3	-0.14	0.22	-0.02	0.15	-0.24	0.06	**0.95**
	SOI4	-0.01	0.23	0.08	0.23	-0.10	0.17	**0.79**

〈Table 3〉 Discriminant Validity: Square Root of AVEs

Variables	HIL	INQ	ITA	ITU	PEOU	PU	SOI
HIL	**0.77**						
INQ	0.17	**0.85**					
ITA	0.34	0.37	**0.78**				
ITU	0.36	0.47	0.51	**0.77**			
PEOU	0.33	-0.02	0.22	0.25	**0.89**		
PU	0.30	0.48	0.46	0.55	0.41	**0.80**	
SOI	-0.17	0.17	0.01	0.14	-0.28	0.05	**0.91**

〈Table 4〉 Discriminant Validity: HTMT Ratios

Variables	HIL	INQ	ITA	ITU	PEOU	PU	SOI
HIL	-						
INQ	0.18						
ITA	0.56	0.42					
ITU	0.48	0.57	0.61				
PEOU	0.42	0.11	0.36	0.29			
PU	0.39	0.54	0.56	0.65	0.45		
SOI	0.21	0.23	0.15	0.22	0.28	0.18	--

trait-monotrait ratio of correlations (HTMT) [Henseler et al., 2015]. All the HTMT values of our constructs are lower than the threshold of 0.85, as shown in 〈Table 4〉.

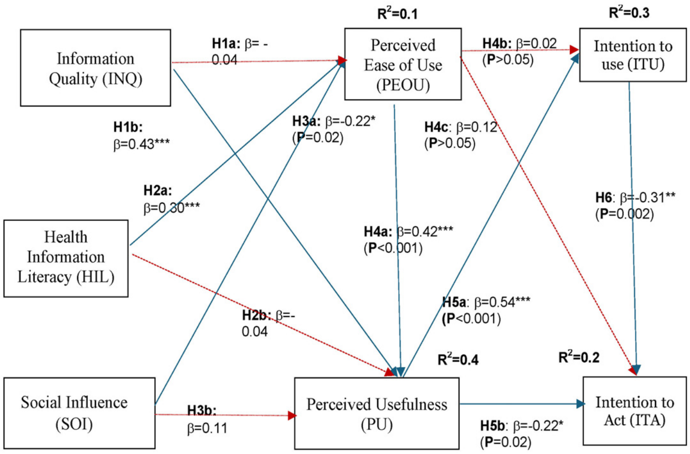
4.2 Structural Model

After validating the measurement model, we assessed the structural model. We followed the 6-step approach of Hair et al. [2020] for assessing 1) the structural model collinearity, 2) the size and significance of path coefficients, 3) R^2 of endogenous variables (in-sample prediction), 4) the f^2 effect size (in-sample prediction), 5) the predictive relevance Q^2 (in-sample prediction), and 6) PLSpredict (out-of-sample prediction).

For step 1, we checked for multicollinearity and found that all VIF values are lower than 2.0, well below the recommended threshold of

〈Table 5〉 VIF Values

	HIL	INQ	ITA	ITU	PEOU	PU	SOI
HIL					1.10	1.30	
INQ					1.10	1.11	
ITA							
ITU			1.73				
PEOU			1.28	1.28		1.29	
PU			2.00	1.28			
SOI					1.11	1.16	



* denotes $p<0.05$, ** denotes $p<0.01$, and *** denotes $p<0.001$
---- denotes the nonsignificant path

〈Figure 2〉 Research Model Results

3.0 [Hair et al., 2019], as shown in 〈Table 5〉.

We assessed the in-sample prediction for steps 2, 3, and 4. We relied on three different metrics [Sarstedt et al., 2014]. We ran the PLS algorithm for steps 2 and 3 to find the path coefficients and the coefficient of determination (R^2). 〈Figure 2〉 shows our structural model results.

As for step 4, we obtained the effect size (f^2) where it is only for endogenous variables and a value of 0.02=〈f^2〈=0.14 is a small effect; a value of 0.15=〈f^2〈=0.34 is a medium effect; and a value of f^2〉0.35 is a large effect [Cohen, 1988]. 〈Table 6〉 shows the effect size of our endogenous variables.

〈Table 6〉 Effect Size of Endogenous Variables

	HIL	INQ	ITA	ITU	PEOU	PU
HIL					0.098	0.016
INQ					0.001	0.33
ITA						
ITU			0.132			
PEOU			0.001	0.001		0.251
PU			0.053	0.353		
SOI					0.056	0.019

For step 5, we ran the blindfolding calculation to assess the Stone-Geisser's Q^2 value [Geisser, 1974; Stone, 1974]. We found that the path model has predictive relevance since the value of Q^2 for all our constructs was greater than zero - the cutoff [Hair et al., 2017]. 〈Table 7〉 shows the results.

〈Table 7〉 Q^2 Results

	SSO	SSE	Q^2 (=1-SSE/SSO)
ITA	990	856.82	0.13
ITU	990	817.58	0.17
PEOU	792	699.49	0.12
PU	990	732.72	0.26

To evaluate our model's predictive performance, in step 6, we ran PLSpredict [Shmueli et al., 2019]. Since some of the indicators of our constructs had higher prediction errors than those of the linear regression model, our model has medium predictive power.

〈Table 8〉 PLSPredict Results

	PLS			LM	
	Q^2predict	RMSE	MAE	RMSE	MAE
ITA1	0.105	0.758	0.611	0.758	0.576
ITA4	0.081	0.903	0.669	0.936	0.696
ITA5	0.073	0.969	0.772	0.978	0.782
ITU1	0.159	0.879	0.675	0.88	0.7
ITU2	0.164	0.913	0.734	0.865	0.692
ITU3	0.104	1.032	0.804	0.999	0.78
ITU4	0.114	0.828	0.65	0.847	0.643
ITU5	0.118	0.882	0.686	0.857	0.653
EOU1	0.079	0.833	0.581	0.856	0.595
EOU2	0.085	0.746	0.523	0.751	0.542
EOU3	0.021	0.759	0.568	0.783	0.591
EOU4	0.123	0.883	0.615	0.898	0.631
PU1	0.091	0.856	0.64	0.882	0.666
PU2	0.167	0.894	0.684	0.924	0.692
PU3	0.164	0.832	0.628	0.853	0.658
PU4	0.111	0.859	0.658	0.886	0.678
PU5	0.139	1.076	0.863	1.079	0.829

Notes: ITA = Intention to Act; RMSE = Root Mean Squared Error; MAE= Mean, Absolute Error; PLS = Partial Least Squares; LM = Linear Regression Model

A summary of the hypotheses findings is shown in 〈Table 9〉.

〈Table 9〉 Summary of Findings for Hypotheses

	Hypothesis	Support?
H1a	INQ will positively affect PEOU.	No
H1b	INQ will positively affect PU.	Yes
H2a	HIL will positively affect PEOU.	Yes
H2b	HIL will positively affect PU.	No
H3a	SOI will positively affect PEOU.	Yes
H3b	SOI will positively affect PU.	No
H4a	PEOU will positively affect PU.	Yes
H4b	PEOU will positively affect ITU.	No
H4c	PEOU will positively affect ITA.	No
H5a	PU will positively affect ITU.	Yes
H5b	PU will positively affect ITA.	Yes
H6	ITU will positively affect ITA.	Yes

4.3 Post-Hoc analysis

To investigate further the nonsignificant relationships. We found that, for H2b and H3b, *PEOU* mediates the impact of *HIL* and *SOI* on *PU*, respectively, rendering their direct impact nonsignificant. As for H4b and H4c, we found that *PU* mediates the effect of *PEOU* on *ITU* and *ITA*, respectively, rendering their direct impact nonsignificant. The results are shown in 〈Table 10〉.

〈Table 10〉 Mediation Analysis

Hypothesis	Relationships	Beta	P-Value
H2b	HIL → PEOU → PU	0.13	0.01
H3b	SOI → PEOU → PU	-0.10	0.053
H4b	PEOU → PU → ITU	0.23	〈0.001
H4c	PEOU → PU → ITA	0.10	0.04

5. Discussion

In this study we found that INQ as a systematic route impacted PU. These results make sense as in health self-assessment type e-health services, the usefulness of the service can be thought to be primarily related to the health information acquired from the application through the results of the assessment; it is similar to a doctor's diagnosis. Hence, INQ, especially the persuasiveness and quality of argumentation, is very critical as a factor [Wollmann et al., 2021; Goetzinger et al., 2007; Zhang et al., 2014] and it contributes to increase positive perception of users to the system [Pai and Huang, 2011]. Regarding the linkage between INQ and PEOU, this hypothesis was rejected in our study, and in this respect our research differs from Lee [2022] who found that INQ of electronic medical records contributed to nurses' PEOU. We believe that the study context, that is, nurses using medical records, is the reason for the divergence from our results.

On the other hand, we found that HIL and SOI as heuristic routes impacted PEOU. The ease-of-use of this kind of self-assessment service can be thought to be primarily related to the progress through the diagnosis questions, that is, the relevance of these questions to the test-taker. As the questions would be more relevant for people with an interest in health and especially in diabetes, those people would be more likely to have higher health literacy and acquaintances who also have health interests. Contrasting the rejected hypotheses (H2b and H3b) with prior literature, we find some differences. In relation to the HIL and PU linkage, Nie et al. [2023] found, different to our study, that HIL connects to PU in the context of mobile health services. We would explain our results with the context of study which is self-health assessment, that is, a specific type of online health service.

As for social influence, this variable appears as "subjective norm" in TAM2 and opposite to our results it is connected to PU, not PEOU, in the model. In this light, our result seems unusual. If we think PEOU to signify the relevance of the diagnosis questions in the self-assessment tool, illustrating the particular characteristic of the context, the possibility arises that individuals who have health interests also have acquaintances with similar interests, and this social connection promotes one's perception of PEOU for the self-assessment tool.

Our study showed that PU is vital in promoting people to adopt the services and plan their healthy activities. Our results are consistent with previous studies where PU has a stronger impact on ITU than PEOU [Yousafzai et al., 2007b; Tao et al., 2020; Tapanainen et al., 2018; Venkatesh et al., 2003]. Indeed, in our research a direct link between PEOU and ITU was not found. This link is well-known from the original TAM and has been typically confirmed in empirical research, though this was not the case with our results. Our result is consistent with the findings of previous studies where the effect of the systematic route (i.e., INQ) on service adoption is stronger than the effect of the heuristic route (i.e., subjective HIL and SOI) [Shi et al., 2020].

Moreover, if users perceive that e-Health services are useful, they are willing to follow health-enhancing behaviors. In our study, if users think the online diabetes test is useful, they will not only use it but also plan health-management activities (e.g., seeking additional information, doing exercises, and changing their diet behavior). Apart from usefulness, ITU also plays an essential role in promoting ITA of users. In fact, not all studies have corroborated this relationship [e.g., Leung and Chen, 2019]; however, our research confirms a positive relationship between ITU of e-Health services and ITA based on the diabetes risk online test service results.

6. Contributions and Implications

6.1 Theoretical contributions

First, our research contributes to the literature on technology adoption by applying HSM in explaining the external factors which could impact PEOU and PU. Previous reviews [Al-Emarn et al., 2018; Legris et al., 2003; Marangunic and Granic, 2015; Yousafzai et al., 2007a] on TAM report that most TAM studies focused on extending the model with external variables. However, the review by

Legris et al. [2003] noted that there is no clear pattern regarding the selection of external variables considered. The result of our study can contribute to solve this problem. Particularly, we found that factors from heuristics cues had a link to PEOU while elements from systematic cues were related to PU.

This can be explained if we look in more detail about what HSM is. According to HSM [Chaiken and Maheswaran, 1994; Zhang et al., 2014], information processing may be selected from two distinct options: heuristic and systematic. The heuristic style minimizes effort in information processing, severely limiting the understanding gained from the information. When individuals encounter cues such as appearance and reputation [Chen and Chaiken, 1999; Eagly and Chaiken, 1993], they may rely on heuristics to quickly assess and determine the ease of using a product or service. For example, if a website has a visually appealing design and a reputable brand, individuals may perceive it as easy-to-use based on these heuristic cues, even without thoroughly analysing its functionality.

Opposite to heuristic processing, systematic processing is accompanied by considerable effort in processing information and therefore brings a good understanding of the object. However, the individual must have high motivation to engage in systematic processing. When individuals encounter cues such as the content of the information [Chen and Chaiken, 1999; Eagly and Chaiken, 1993], they are more likely to engage in systematic processing, carefully evaluating the content and functionality of the product or service. By doing so, they can better understand its usefulness and make judgments based on a more comprehensive analysis.

Second, our research is the first to extend HSM's application to online healthcare services. Particularly, we found that the heuristic path (including HIL and SOI) influenced PEOU, while the systematic path (i.e., INQ) affected patients' usefulness perception. The systematic path is clearly dominant in the context of online diabetes risk test acceptance. This is due to two reasons: 1) the sole influence of the systematic path (INQ) to PU, and onward to ITU and ITA; and 2) hypotheses about the linkages of PEOU to ITU and to ITA are not supported.

According to HSM, individuals will often start with heuristic processing. However, in healthcare services, which are directly linked to well-being and healthcare, people will be more careful. Thus, they will more often select the systematic path than the heuristic path to start their decision-making process. Our finding emphasizes the importance of the systematic path, especially in considering the adoption of e-Health services. In addition, by applying HSM, we confirm the different impact levels of PU and PEOU in technology adoption [Yousafzai et al., 2007b; Tao et al., 2020; Tapanainen et al., 2018; Venkatesh et al., 2003]. Moreover, our results strengthen the previous finding that while PEOU does not directly impact ITU, its impact is mediated by PU [Holden and Karsh, 2010; Yarbrough and Smith, 2007; Venkatesh et al., 2003].

6.2 Practical Contributions

First, the systematic cues including INQ could strongly impact the user's perception regarding service usefulness. Indeed, in the healthcare area, in contrast to e-Commerce, users' needs are related to the information gained from the service [Ghasemaghaei and Hassanein, 2015]. Therefore, information is crucial as a quality factor in healthcare [Wollmann et al., 2021] and is particularly relevant for online healthcare services, where there is no direct personal contact with physicians. It is imperative that e-Health services provide users with sufficient information to make informed decisions and engage in appropriate self-help activities for their symptoms. Information characteristics such as completeness, relevance, sufficiency, clarity, and accuracy should be enhanced as these informational attributes are linked to patient decision-making [Dutta-Bergman, 2004; Eysenbach et al., 2002; Hu and Sundar, 2010].

Second, the heuristic cues, including subjective HIL and SOI could influence how people perceive the ease-of-use of e-Health services. Understanding the impact of these heuristic cues on users' PEOU is crucial for designing effective e-Health services. By acknowledging the significance of subjective HIL and leveraging positive SOI, service providers can tailor their offerings to match users' expectations and create a user-friendly experience. This may involve designing intuitive interfaces, providing clear instructions, and incorporating social elements that facilitate information sharing and social support within the e-Health service.

To enhance subjective HIL we need to focus on measures for improving people's information skills and competencies besides their ability to use specific systems and technologies and health-related knowledge. This can be achieved through systematic educational interventions and informing and providing users independent guidance. A relevant parallel approach to improve the match between HIL and e-health services is to take account of users' current level of HIL and factors that make them lack confidence about their health information.

Finally, the critical link between ITU and ITA shows the importance of adopting e-Health services and positive self-health management activities. Our research implies that the adoption of e-Health assessment tools is linked to the ITA for better health conditions especially for people who might have a high risk of developing a disease. In this way, using these assessment tools is important for better understanding one's health condition, leading to concrete actions to mitigate the disease or risk of disease. Thus, it is vital to promote e-Health service adoption since this might, in turn, positively promote active self-health management behaviors.

7. Limitations

Our research is subject to certain limitations that need to be acknowledged. Firstly, a notable challenge is the lack of a universally accepted and validated measurement for Health Information Literacy. This issue aligns with ongoing debates in information studies [Symolka et al., 2022; Hicks and Lloyd, 2021] regarding the quantifiable and measurable skills in HIL and other information literacies, as well as the contextual competencies that may not be easily transferable or measurable across different populations and contexts. Additionally, it is important to note that the data used in our study was obtained from a single popular online healthcare service. These limitations highlight the need for further research and validation of HIL measurement tools, as well as the importance of replicating our findings across diverse online service platforms. By addressing these limitations, future studies can provide a more comprehensive understanding of the relationships between cues, user perceptions, and the effectiveness of online services.

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〈Appendix〉

Variables	Items	Sources
Social Influence (SOI)		Venkatesh et al. [2003]
SOI1	People who influence my behavior think that I should use the service	
SOI2	People who are important to me think that I should use the service	
SOI3	People who I appreciate would encourage me to use the service	
SOI4	People who I spend much time with would think using the service is a good idea	
Information Quality (INQ)		Kim and 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 (Removed)	
Perceived Ease-of-Use (PEOU)		
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	
Subjective Health Information Literacy (HIL)		Niemelä et al. [2012]
HIL1	I like to get health information from a variety of sources	
HIL2	I know whether to seek health information	
HIL3	I apply health related information to my own life and/or that of people close to me	
Words of Mouth (WOM)		Hamari and 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 [1989], Davis [1993]
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	
ITA2	Discuss with family or friends about the services (Removed)	
ITA3	Make an appointment to see a specialist (Removed)	
ITA4	I plan to increase the number of physical activities	
ITA5	I plan to change my diet behavior	

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Hai Nguyen Thi Thanh obtained her bachelor's degree from the National Economics University of Hanoi, Master of Commerce from the Sydney University, and PhD from the Waseda University, Japan. She is currently teaching in MBA Global in the University of South Wales and working in different international research projects regarding information systems management. Her research focuses on information system adoption, dynamic capabilities and strategies and e-health. Together with her colleague, her work has appeared in the Computers in Human Behavior, Information Processing and Management, International Journal of Medical Informatics, and Journal of Information Systems for Developing Countries.

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