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Development and validation of the quality of online health information seeking: Psychometric properties and a confirmatory factor analysis

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ABSTRACT
This study aims to investigate the development and validation of all items and dimensions for the quality of online health information seeking (QHIS), which was assessed using a five-point interval self-report rating measure. This measure is proposed to evaluate the quality of online health information seeking among Malaysian consumers through confirmatory factor analysis (CFA). A total of 392 responses were collected from Malaysian consumers using the simple random sampling method. The pooled-CFA procedures were conducted to validate all dimensions at once. When the findings were acquired, the study performed the validation procedure for construct validity, convergent validity, composite reliability and discriminant validity. Results from CFA confirmed the validity of the QHIS measure by generating good data-model fit statistics characterised by strong latent construct and internal reliability estimates. Based on the self-reported scores, it also concluded that the QHIS scale had good convergent validity. The findings also reported that composite reliability and discriminant validity for all latent constructs in QHIS had been achieved accordingly. These findings present initial justification indicating that QHIS is reliable and valid and can be utilised to assess the quality of online health information seeking among Malaysian consumers. Limitations are explored, and recommendations for future research and practice are provided.

Keywords: Information seeking; E-health; Health information; Information quality; Psychometric properties; Confirmatory Factor Analysis.

INTRODUCTION

The tidal wave of infrastructures and "infostructures" innovations in health information technology which has become a veritable tsunami during the past few years, has been significant throughout most continents, including Asia, Europe, Australia and North

America, fused by a determination to optimise the quality, safety and efficiency of patient care. This proliferation has resulted in many positive social and managerial outcomes and improves service administration, clinical practice, policy, and research through the availability of relevant data and evidence (Galetsi et al. 2022). Using digital tools to make decisions becomes particularly relevant in the healthcare industry since decisions are generally based on physicians' expertise (Basile et al. 2022). Medical practitioners have started to employ apps and other digital technologies as part of their profession, and medical students are frequently utilising a range of applications for their education, such as reference tools, question banks, and anatomical atlases (Galetsi et al. 2022; Ellaway et al. 2014). What is more, e-health utilisation by patients and consumers is progressively expanding. This situation is presumably owing to the patients being empowered by physicians and the health system (Eysenbach and Köhler 2002; Fox et al. 2005; Oh and Lee 2012; Tan and Goonawardene 2017). Leung and Chen (2019) reported several main activities for which individuals engage in health-related information platforms and online apps, including seeking health information, sharing health-related experiences, attending health tutorials, self-monitoring, asking about medical services and setting reminders.

The impact of emerging smart technology-driven healthcare innovations, including clinical decision support systems (CDSS), information technology-based assistive services, electronic medical record (EMR) systems, computerised physician order entry (CPOE), telemedicine services, artificial intelligence (AI), 5G technology, smart health applications, big data, cloud computing, blockchain, Internet of Things, smart wearable devices, robotics and mobile health (m-health) has taken centre stage in supporting the delivery of healthcare and has been documented in the scholarly literature (Iyanna et al. 2022; Chitungo et al. 2021; Heath and Porter 2019; Zobair, Sanzogni and Sandhu 2020). Moreover, recent studies (Fagherazzi et al. 2020; Mbunge et al. 2021; Azam and Usman 2021; Wang et al. 2021) stressed the necessity of using modern technology to deliver healthcare services remotely. These developments have significantly enhanced medical care management and diagnostics (Choi et al. 2019). However, they have not diffused as anticipated based on their multiple benefits (Iyanna et al. 2022).

Furthermore, the emergence of the COVID-19 pandemic in 2020 has added other dimensions to the puzzle. Indeed, the pandemic outbreak and the subsequent restrictions on movements not only created a number of economic and non-economic difficulties all over the world (Laato et al. 2020; Talwar et al. 2021) but also had a profound impact on individual attitudes and behaviours (Ghobadian et al. 2022; Mohammed and Ferraris 2021), including the need of information to understand the health-risk situation and dispel panic (Guitton 2020). This situation is undoubtedly relevant in the healthcare industry, as the pandemic offered the exceptional obstacle of safely providing care to consumers who suffered from illnesses other than COVID-19 infections (Iyanna et al. 2022). In this context, seeking health information online enables the proper use of digital innovations or e-health solutions such as telehealth (Monaghesh and Hajizadeh 2020), which consequently leads to providing health services and medical care more widely than before (Wax and Christian 2020; Duplaga and Turosz 2022).

Health information seeking (HIS) is how individuals receive information to learn about health, disease, health threats, and health promotion (Lambert and Loiselle 2007; Zhao and Zhang 2017). HIS is also interpreted as verbal or nonverbal behaviour as well as an online method for acquiring, elaborating on, and confirming information or knowledge regarding a specific topic (Manafo and Wong 2012), or the means by which people access information about their health, health promotion initiatives, and health and disease risks.

It might be active or obligatory and is carried out in response to a new medical condition or diagnosis (Zimmerman and Shaw 2020). Different populations seek health information for various purposes. Effective health information seeking could contribute to health-improving practices and act as a crucial tool for comprehending how individuals obtain health information and boosting awareness of health risk factors (Chaudhuri et al. 2013). However, the health issue continues to heighten due to a lack of access to health information. Thus, a strategy to alleviate the disease's burden might be improving individuals' health information seeking (Gedefaw, Yilma and Endehabtu 2020). Moreover, Park et al. (2014) recognised that there were still limited studies that focused on understanding the factors underlying the intentions to seek information on digital platforms. Therefore, it is crucial to have a comprehensive understanding of the factors that contribute to the effectiveness of online health information seeking in providing health information efficiently, that is, to provide the appropriate information to the right individuals using the right platforms.

The factors and antecedents identified by researchers were several: socio-demographic characteristics such as age (Abdoh 2022; Liu, Whitener and Hwang 2023; Kehoe et al. 2022), gender (Dol et al. 2022), educational status (Abdoh 2022), and income (Chu et al. 2022), comorbidity (Merati-Fashi, Dalvandi and Yekta 2022; Park et al. 2022), health literacy (Park et al. 2022; Chu et al. 2022; Gulec, Kvardova and Smahel 2022) and perceived trust (Gulec et al. 2022). Researchers have also explored how individuals' social networks and informational support from families and friends impact HIS (Kehoe et al., 2022; Pretorius, McCashin and Coyle 2022). In addition, information quality has also been recognised as a factor that can influence individuals' engagement with or aversion to information (Afful-Dadzie and Anthony 2021). Moreover, researchers have discovered resistance from various stakeholders to various innovations and advances in digital healthcare technologies, including healthcare information technologies (HIT) or electronic health (Kelly et al. 2017; Sarradon-Eck et al. 2021; Talwar et al. 2021). This resistance then resulted in challenges in employing online health information seeking. Underlying this resistance is the reality that health information seeking also includes numerous threats, as previous research has highlighted in many scenarios (Bresciani et al. 2021). Therefore, from surveying the literature on health information seeking, the results suggest that it should be conceptualised as a multi-dimensional construct.

The Quality of Online Health Information Seeking tool (QHIS) was developed based on the twelve dimensions derived from three theoretical models that have been incorporated as the foundation of the hypothetical model in this study. The three theoretical models are The Unified Theory of Acceptance and Use of Technology (UTAUT), the Health Belief Model (HBM) and the DeLone & McLean Information Systems Success Model (ISSM). UTAUT model is employed to measure the e-health technology acceptance, while HBM is implemented to assess the health behaviour, in this case, health information seeking. Finally, ISSM is adopted to measure the quality attributes in the system, at the same time ensuring the success of the system. The necessity of integrating the three models, particularly in the consumer context, with the purpose of expanding its theoretical applicability, predicting health behaviour and developing a deeper cognitive comprehension of system usage behaviour. A comprehensive view of the links between technology acceptance, health behaviour and system success factors was also established. It is acknowledged that each model has its own designed instrument. Most of the research in the domain of health information seeking and e-health applies just one of these models (Alam et al., 2020; Hossain, Quaresma and Rahman 2019; Rahi, Khan and Alghizzawi 2021; Xia, Deng and Liu 2017). To summarise, standalone models have lacked a holistic explanation of user behaviour (Baptista and Oliveira, 2015). Through a review of the literature, it is evident that there are various acknowledged measures of health information seeking available; many of these capture aspects of each of the three components: technology acceptance, health behaviour, and quality. However, no attempts have been made to measure all three components together. Furthermore, none of these measures has been reported in the literature to have been validated using confirmatory factor analysis (CFA). Therefore, this QHIS measure comprises several interrelated components from these three theoretical models mentioned above: effort expectancy, performance expectancy, social influence, facilitating condition, perceived disease threat, self-efficacy, perceived barriers, information quality, service quality, and system quality. The purpose of this study is to establish the reliability and convergent validity of the QHIS in a sample of Malaysian consumers, to evaluate the factor structure of the QHIS using a confirmatory factor analysis (CFA) and lastly, to explore the convergent validity of the QHIS.

METHOD

Development of Instrument

A structured questionnaire was adapted and modified from sixteen different studies. It comprised seventy-six (76) items earlier on. Both pre-test and pilot studies were conducted to obtain approval for the "modified items" before utilising them in the final survey, especially when the industries and cultures differ from the population for which the original instrument was built. Fine-tuning of the questionnaire was done when the pre-test was conducted. The pre-test began with expert validation, consisting of three major processes: content validity, face validity, and criterion validity. Then, the exploratory factor analysis (EFA) was performed on the sample (N= 120, 56.5% women, 53.2% aged 30-39 years old) using Principal Component Analysis (PCA) procedures with Varimax rotation (Gaskin and Happell 2014) since this rotation method extracts factors in accordance with the items' correlation. Preliminarily, Kaiser-Meyer-Olkin (KMO) was used to assess sampling adequacy, and the Bartlett test of sphericity was used to examine the factorability of the data. Internal consistency was computed using Cronbach's alpha on the dimensions extracted by the factor analysis, which ranged between 0.781 and 0.923, suggesting that the items representing the dimensions are highly reliable and highly acceptable (Kline 2015). Sixty-three (63) items remained in the questionnaire after thirteen items were deleted during EFA, which were cross-loaded on multiple components with a factor loading below 0.60.

These items were formulated using a five-point interval scale, ranging from 1 = 'strongly disagree' and 'never' to 5 = 'strongly agree' and 'always'. All the items for the three dimensions, namely information quality, system quality, and service quality, were adapted from studies (DeLone and McLean, 1992; Gable, Sedera and Chan 2008; Rai, Lang and Welker 2002). Information quality and system quality were measured using a 7-item measure, while service quality was measured using a 6-item measure. These dimensions cover the quality of e-health systems' output, the system's performance from a technical and design perspective, and the overall support delivered by the service provider. It is assumed that these three dimensions would explain the quality and success factors in supporting online health information seeking.

Performance expectancy was measured using a 4-item measure (Davis 1989; Davis, Bagozzi and Warshaw 1989; Rosenstock 1974; Venkatesh, Thong and Xu 2012). In a broader sense, this dimension is defined as an individual's evaluation of the positive things that will happen as a result of enacting health behaviour, to be specific, health information seeking. Both effort expectancy and facilitating conditions were measured using a 4-item measure adapted from Venkatesh et al. (2012). Effort expectancy is associated with how easy it is to use an e-health system. At the same time, facilitating conditions describe the consumers' perceptions of the technical and organisational infrastructure required to use and support an e-health system. Social influence was also measured using a 5-item scale (Rosenstock 1974; Venkatesh et al. 2012). This dimension consists of prompts that will trigger or persuade consumers to use the e-health system. It is suggested that when users are presented with new technology, these four factors will influence their decision about how and when they will use it.

In the context of health behaviour, online health information seeking is regarded as an action to maintain, attain, or regain good health and prevent illness. There are three dimensions involved. Firstly, perceived disease threat was measured using a 4-item measure adapted from (Liang, Xue and Chase 2011). The perceived barrier was also measured using a 4-item measure established by Liebermann and Stashevsky (2002), and self-efficacy was measured using a 4-item measure (Rosenstock 1974; Venkatesh et al. 2012).

Behavioural intention is defined as individuals' intentions to seek health information in the near future. This dimension was measured using a 5-item measure adapted from Taylor and Todd (1995). Finally, technology use is referred to as the use of the Internet for health information seeking. Consumers will be motivated to use the Internet when they believe it is useful for providing information on health and health management. The dimension was measured using a 9-item scale established by Hale et al. (2010), Kim and Park (2012), and Yoo and Robbins (2008). Table 1 presents the twelve dimensions for measuring HIS construct and their items.

Sample and Procedures

A cross-sectional design was implemented to conduct the study. A total of 500 questionnaires were distributed to Malaysian consumers from diverse backgrounds,cultures and may also differ in demographic and educational characteristics in five Malaysian states, including Pulau Pinang, Kuala Lumpur, Selangor, Melaka, and Johor, based on simple random sampling from hospitals and universities. The online survey method is employed to allow the respondents to attend to the questionnaires without any pressure so that the responses reflect the respondents' genuine opinions. Therefore, response bias due to time constraints and researcher's presence did not arise. An email invitation to participate in this study with the link address to access Google Forms was sent to the participants. Participation was voluntary, and confidentiality was assured. The consumers were informed that the data collection was anonymous and that they could omit any information they did not wish to give as well as withdrawing from the study at any time. A total of 392 completed questionnaires were returned (response rate of 78.4%). Then, all the data were gathered and analysed.

Table 1: Dimensions and Items Measuring Health Information Seeking Construct

Dimension	Item	Statement
Information Quality (IQ)	IQ1	E-health systems provide an output that seems to be exactly what is needed.
	IQ2	Information needed from e-health systems is always available.
	IQ3	Information from e-health systems is easy to understand.
	IQ4	Information from e-health systems appears readable, clear, and well-formatted.
	IQ5	E-health systems give a lot of information clearly and in a few words, brief but comprehensive.
	IQ6	Information from e-health systems is always timely and up-to-date.
	IQ7	E-health systems provide sufficient information to help regarding your health questions or problems.
System Quality (SQ)	SQ1	Data from e-health systems is the most recent.
	SQ2	E-health systems are easy to use.
	SQ3	E-health systems are easy to learn.
	SQ4	E-health systems include necessary features and functions.
	SQ5	The e-health systems user interface can be easily adapted to one's personal approach.
	SQ6	The e-health systems are always up-and-running as necessary.
	SQ7	All data within e-health systems are fully integrated and consistent.
Service Quality (SV)	SV1	When you have a problem, the e-health systems service shows a sincere interest in solving it.
	SV2	The e-health systems service is always willing to help you.
	SV3	You feel safe in your sharing with the e-health systems service in terms of privacy protection.
	SV4	The e-health systems service has the knowledge to answer your questions.
	SV5	The e-health systems service gives you individual attention.
	SV6	The e-health systems service understands your specific needs.
Performance Expectancy (PE)	PE1	Using e-health systems will support critical aspects of my health care.
	PE2	Using e-health systems will enhance my effectiveness in managing my health care.
	PE3	Using e-health systems will enhance the level of convenience in seeking health information.
	PE4	Using e-health systems will enhance the quality of life.
Effort Expectancy (EE)	EE1	Learning how to use e-health systems is easy for me.
	EE2	My interaction with e-health systems is clear and understandable.
	EE3	I find e-health systems simple and easy to use.
	EE4	It is easy for me to become competent in using e-health systems.
Social Influence (SI)	SI1	People who are important to me think that I should use e-health systems.
	SI2	People who influence my behaviour think that I should use e-health systems.
	SI3	People whose opinions I value prefer that I use e-health systems.
	SI4	Medical care personnel encouraged and supported me in using e-health systems.
	SI5	The media endorses the use of e-health systems.
Facilitating conditions (FC)	FC1	I have the necessary resources (e.g. internet devices, internet speed, data processing capabilities) to use e-health systems.
	FC2	I have the knowledge necessary to use e-health systems.
	FC3	E-health systems are compatible with other technologies (e.g. smartphones, tablets, PC) that I use.
	FC4	I can get help from others when I have difficulties using e-health systems.
Perceived Disease Threat (PDT)	PDT1	Seeking health information online could be misleading.
	PDT2	Seeking health information online could harm my health.
	PDT3	I could make the wrong decisions regarding my health based on the poor quality of online health information.
	PDT4	I could be stressed out because of exaggerating online health information.
Perceived Barriers (PB)	PB1	I am worried about seeking health information online because it provides inappropriate health information.
	PB2	I am worried about seeking health information online because the information found online is not reputable, out-of-date or inaccurate.

Dimension	Item	Statement
	PB3	I would not feel secure sending sensitive information online.
	PB4	On the whole, considering all sorts of factors combined, it would be risky to seek health information online.
Self-efficacy (SE)	SE1	I think that I take health into account a lot in my life.
	SE2	I think it is important to know well how to stay healthy.
	SE3	I have set several definite goals to improve my health.
	SE4	I consider myself very health conscious.
Behavioural Intention (BI)	BI1	I have a high intention to seek online health information.
	BI2	I will seek online health information in the near future.
	BI3	I will recommend others to seek online health information.
	BI4	I will share the information with others.
	BI5	I will recommend others to use health information online.
Technology Use (TU)	TU1	I use the Internet to get general health information.
	TU2	I use the Internet to get information on medicine/drugs.
	TU3	I use the Internet to be equipped with information before/after a doctor's appointment.
	TU4	I use the Internet to get descriptions of various diseases.
	TU5	I use the Internet to get information on treatments/therapy/ diagnosis.
	TU6	I use the Internet to get information on how to care for myself.
	TU7	I use the Internet to understand how to deal with an illness.
	TU8	I use the Internet to get information on hospitals/clinics/other health care facilities.
	TU9	I use the Internet to get information on health management (exercise, diet, nutrition, stress, mental health, etc.).

Statistical Analysis for Validation

Descriptive statistics (frequencies, percentages) were performed to describe the participants' socio-demographic characteristics. Assessment of the skewness and kurtosis provides an indication of normality. The measure of skewness and kurtosis reflects the normality assessment for every item, while the value of multivariate kurtosis reflects the multivariate normal distribution for data sets. The factorial structure of the measurement model was evaluated using confirmatory factor analysis (CFA). This study combines all of the constructs to perform the Pooled-CFA. The pooled-CFA procedure was employed because it is efficient, fast and accurate, as well as a one set of fitness indexes for all constructs in the model that could be monitored simultaneously.

The measurement model of latent constructs is compulsory to meet the three types of validity requirements, namely Construct Validity, Convergent Validity, and Discriminant Validity. The Construct Validity is assessed through the Fitness Indexes of the Measurement Model, while the Convergent Validity is evaluated through an assessment of item factor loadings and their statistical significance, followed by an assessment of the factors' average variance extracted (AVE) and construct reliabilities (CRs). Convergent Validity is indicated by an item factor loading ≥ 0.5 and $p < .05$ (Hair et al. 2018), AVE ≥ 0.5, and CR ≥ 0.7 (Fornell and Larcker 1981). AVE and CR values were calculated according to the equations in Figure 1 given by Fornell and Larcker (1981).

$$\mathrm{CR} = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \left(\sum_{i=1}^{n} e_i\right)},$$

$$\mathrm{AVE} = \frac{\sum_{i=1}^{n} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} e_i},$$

Figure 1: Equations for the Calculation of CR and AVE values (Fornell and Larcker 1981)

where λ_i is the factor loading for item *i* under a particular construct, and e_i is the error variance for the item. Raykov (1997; 1998) described a procedure to obtain better estimates of the CR values and confidence intervals in the context of SEM in the AMOS software environment. The procedure was performed as follows: (1) a latent reliability variable (RV) was created for each factor; (2) directional paths were added from the items to the respective RVs; (3) the regression weights for these additional paths were all set to 1; and (4) the square of the correlation coefficient between a particular factor and its RV is the composite reliability coefficient for that factor.

Next, discriminant validity was evaluated by comparing factor AVE values with shared variances (SVs) between the factors, which are the squared correlations between any two factors. The factors were considered discriminant when the AVE values were greater than the SV values (Fornell and Larcker 1981). Model revisions were conducted based on assessments of factor loadings, standardised residuals (SRs), and modification indices (MIs), while maintaining the congenericity of the measurement model within the theoretical framework. Items with factor loadings < 0.5 were considered for removal (Hair et al. 2018). In this study, MI values were only used to identify potential cross-loading items (Hair et al. 2018) without setting any particular cutoff values, as the decision based on SR values was given more importance. When it comes to reliability, this study determines to assess the Composite Reliability (CR) for analysis using Structural Equation Modeling (SEM) instead of the traditional method of generating the Cronbach Alpha.

Multiple fit indices were examined to assess how well the model fit the data based on the recommended cutoff and range scores. Kline (2015) suggested interpreting a good fit to be a non-significant chi-square. However, a significant chi-square value can be sensitive to discrepancies in model fit, especially in large sample sizes (Byrne 2012; Kline 2015). Byrne (2012) also recommended the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) be >0.90 for a good fit, and values >0.95 indicate a very good fit. The Root Mean Square Error of Approximation (RMSEA) values <0.05 suggest good model fit, and values up to 0.08 indicate adequate model fit considering narrow confidence intervals. When considering model accuracy, fit indices should be interpreted as guidelines that also account for theoretical, statistical, and practical considerations (Byrne 2012). Data analyses were performed using IBM-SPSS-AMOS version 25.0 for Windows. The level of significance was set at $p < 0.05$.

The readability of the instrument is also assessed using the Flesch Reading Ease (FRES) readability test. The Flesch Reading Ease formula was selected because it is the most reliable method (Klare 1963; Mohammed et al. 2023). Rudolph Flesch developed this formula to evaluate the context-related difficulty of text documents. It serves as an indicator for determining how challenging it can be to comprehend reading material in English. The text content will be graded according to a number of characteristics, including letters, syllables, word form, word length and sentence length. Figure 2 presents the algorithm to determine Flesch reading ease (Eleyan, Othman and Eleyan 2020) which involves: (1) calculating the average number of words used per sentence; (2) calculating the average number of syllables per word; (3) multiplying the average number of syllables per word multiplied by 84.6 and subtract it from the average number of words multiplied by 1.015; and (4) subtracting the result from 206.835. As illustrated in Table 2, this algorithm generates scores that indicate the text's degree of readability (Eleyan, Othman and Eleyan 2020).

Flesch Reading Ease Formula:

$$FRES = 206.835 - (1.015 \times ASL) - (84.6 \times ASW)$$

where:

$$\text{ASW} = \text{average number of syllables per word} = \frac{number\ of\ syllables}{number\ of\ words}$$

Figure 2: Flesch Reading Ease Formula (Eleyan, Othman and Eleyan 2020)

Table 2: Flesch Reading Ease Score

Score	School Level	Notes
100.0-90.0	5th Grade	Very easy to read. Easily understood by an average 11-year-old student.
90.0-80.0	6th Grade	Easy to read. Conversational English for consumers.
80.0-70.0	7th Grade	Fairly easy to read.
70.0-60.0	8th and 9th Grade	Plain English. Easily understood by 13- to 15-year-old students.
60.0-50.0	10th to 12th Grade	Fairly difficult to read.
50.0-30.0	College	Difficult to read.
30.0-10.0	College Graduate	Very difficult to read. Best understood by university graduates.
10.0-0.0	Professional	Extremely difficult to read. Best understood by university graduates.

RESULTS

The Demographic Profile

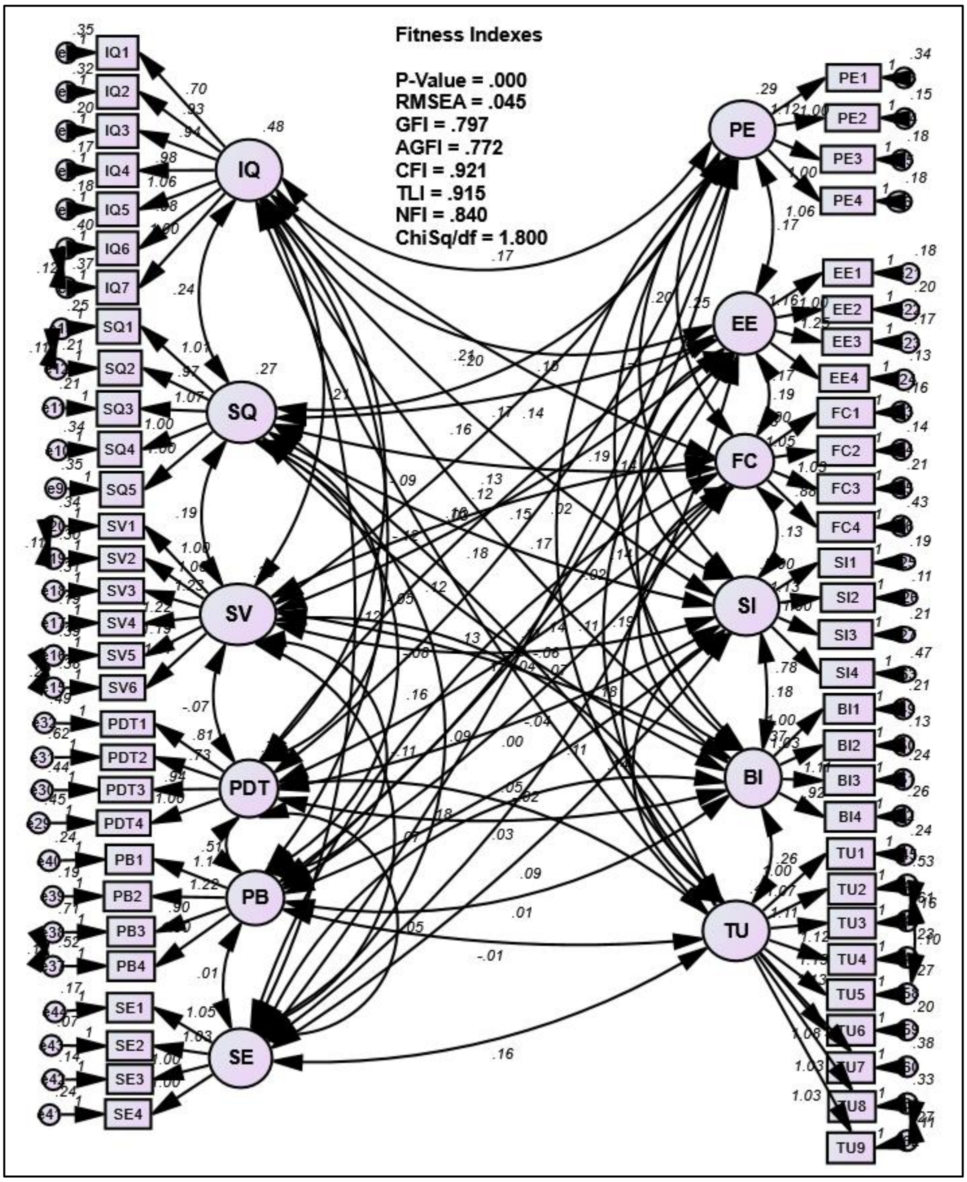
Table 3 demonstrates the demographic profiles of the respondents. Participants were 294 females and 98 males. More than half of the participants were between 30 – 39 years old (53%), while 22 percent were between 40 – 49 years old, 21 percent were between 20 – 29 years old, and 4 percent were aged 50 years old and above. The majority of the participants (94%) graduated from university, 4 percent were college graduates, and the remaining were high school graduates (2%). Approximately 64 percent of the participants were married, the remaining 34 percent were single, and only 2 percent were widows/widowers/divorcees. Most participants often sought online health information (36%) and spent less than 30 minutes accessing online health information each time (41%). Most of them are also highly interested in health information (53%), although they do not have any health problems (63%).

Table 3: Summary of Respondents' Demographics Information

Questions on……..	Category	Frequency	Percentage (%)
Gender	Male	98	25
	Female	294	75
Age	20 – 29 years old	81	21
	30 – 39 years old	206	53
	40 – 49 years old	88	22
	≥ 50 years old	17	4
Marital status	Single	134	34
	Married	250	64
	Widower/widow/divorcee	8	2
Education level	Secondary school	9	2
	College	17	4
	University	366	94
Frequency of seeking online health information	Always	108	28
	Often	141	36
	Sometimes	131	33
	Rarely	12	3
Average time of accessing online health information each time	Less than 30 minutes	161	41
	30 – 59 minutes	159	41
	1 – 2 hours	47	12
	2 hours or more	25	6
Interest in health information	Low	12	3
	Moderate	171	44
	High	209	53
Do you have a health problem?	Yes	103	26
	No	245	63
	Don't know	44	11

Confirmatory Factor Analysis

In order to evaluate the normality of the measurement model, we proceeded with the evaluation of skewness and kurtosis indices. These indices revealed that all of the items were normally distributed with values for skewness are ranged from -1.138 to 0.235. If the skewness value is 1.0 or lower, it demonstrates data normality. Meanwhile, the kurtosis values ranged from -0.981 to 2.459, fulfilling the kurtosis values of -3.0 to 3.0 for data to be considered normal. The value of multivariate kurtosis is 42.427 which demonstrates the multivariate normal distribution for the data sets. Therefore, the assumption of normality for the construct has met the requirement for parametric statistical analysis such as correlation, regression and structural equation modelling (Kline 2015). The measurement model was tested by computing CFA. The first analysis demonstrated a dissatisfactory result as the measurement model did not have a satisfying fit based on the fit indices. To obtain a good-fitting model, this model was revised iteratively. The researchers tried to keep three or more items per factor to maintain a reasonable number of representative items. The removal of four items (SQ1, SQ7, SI4, BI5) with factor loadings of less than 0.6 has resulted in the best improvement to the model. Figure 3 demonstrates the revised output of CFA, which illustrates the factor loading for every item, the factor loading for every component, and the correlation between the constructs.



Names of factors: IQ=Information Quality; SQ=System Quality; SV= Service Quality; PE=Performance Expectancy; EE= Effort Expectancy; SI= Social Influence; FC=Facilitating Conditions; PDT= Perceived Disease Threat; PB= Perceived Barriers; SE= Self-Efficacy; BI=Behavioural Intention; TU=Technology Use

Figure 3: The CFA Model with Unstandardised Estimates (revised)

Based on the analysis, all the fitness indexes have achieved the threshold values. Table 4 represents the fitness indexes that reflect the construct validity for the measurement model. The Absolute Fit category, namely Root Mean Square Error of Approximation (RMSEA), is 0.045 (achieved the threshold of less than 0.08). The Incremental Fit category, namely Comparative Fit Index (CFI), is 0.921 (achieved the threshold of greater than 0.90), and the Parsimonious Fit category, namely the ratio of Chi-Square Fit Statistics/Degree of Freedom (Chisq/df), is 1.800 (achieved the threshold of less than 3.0).

Table 4: The Fitness Indexes for the Measurement Model

Name of category	Name of index	Level of Acceptance	Index value
Absolute fit	Root Mean Square Error of Approximation (RMSEA)	RMSEA < 0.08	0.045
Incremental fit	Comparative Fit Index (CFI)	CFI > 0.85 (ideal > 0.90)	0.921
Incremental fit	Tucker-Lewis Index (TLI)	TLI > 0.85 (ideal > 0.90)	0.915
Parsimonious fit	Chi-Square Fit Statistics/ Degree of Freedom (Chisq/df)	Chi-square/ df < 5.0 (ideal < 3.0)	1.800

Convergent Validity and Composite Reliability

For the assessment of Convergent Validity, the values of Average Variance Extracted (AVE) and Composite Reliability (CR) were computed. According to Table 5, all AVE and CR values exceed their threshold values of 0.5 and 0.6, respectively. However, there were four items that did not function optimally due to low factor loadings. These items are SQ1 ("Data from e-health systems is the most recent."), SQ7 ("All data within e-health systems are fully integrated and consistent"), SI4 ("Medical care personnel encourage and support me to use e-health systems") and BI5 ("I will recommend others to use health information from online."). The two items were consequently deleted to further improve the model fit.

Table 5: The Average Variance Extracted (AVE) and Composite Reliability (CR)

Construct	Item	Factor Loading	CR (Above 0.6)	AVE (Above 0.5)
Information Quality (IQ)	IQ1	0.632	**0.914**	**0.604**
	IQ2	0.754		
	IQ3	0.825		
	IQ4	0.854		
	IQ5	0.864		
	IQ6	0.733		
	IQ7	0.751		
System Quality (SQ)	SQ1	deleted	**0.836**	**0.506**
	SQ2	0.722		
	SQ3	0.737		
	SQ4	0.770		
	SQ5	0.662		
	SQ6	0.658		
	SQ7	deleted		
Service Quality (SV)	SV1	0.703	**0.892**	**0.580**
	SV2	0.744		
	SV3	0.787		
	SV4	0.851		
	SV5	0.739		
	SV6	0.737		
Performance Expectancy (PE)	PE1	0.679	**0.860**	**0.606**
	PE2	0.838		
	PE3	0.783		
	PE4	0.805		
Effort Expectancy (EE)	EE1	0.762	**0.886**	**0.661**
	EE2	0.795		
	EE3	0.838		
	EE4	0.854		
Social Influence (SI)	SI1	0.863	**0.898**	**0.691**
	SI2	0.934		
	SI3	0.852		
	SI4	deleted		
	SI5	0.650		

Construct	Item	Factor Loading	CR (Above 0.6)	AVE (Above 0.5)
Facilitating Condition (FC)	FC1	0.841	**0.871**	**0.630**
	FC2	0.865		
	FC3	0.811		
	FC4	0.638		
Perceived Disease Threat (PDT)	PDT1	0.714	**0.824**	**0.541**
	PDT2	0.639		
	PDT3	0.781		
	PDT4	0.798		
Perceived Barriers (PB)	PB1	0.887	**0.883**	**0.657**
	PB2	0.916		
	PB3	0.661		
	PB4	0.751		
Self-efficacy (SE)	SE1	0.825	**0.900**	**0.693**
	SE2	0.907		
	SE3	0.834		
	SE4	0.758		
Behavioural Intention (BI)	BI1	0.797	**0.881**	**0.649**
	BI2	0.869		
	BI3	0.812		
	BI4	0.740		
	BI5	deleted		
Technology Use (TU)	TU1	0.812	**0.938**	**0.628**
	TU2	0.712		
	TU3	0.700		
	TU4	0.848		
	TU5	0.831		
	TU6	0.865		
	TU7	0.769		
	TU8	0.776		
	TU9	0.805		

Discriminant Validity

Discriminant validity is established when each construct is distinct from others; therefore, it does not measure the same thing (Hair et al. 2021). In other words, the assessment of discriminant validity ensures that no redundant constructs occur in the model. Specifically, when any pair of constructs in the model are highly correlated, a redundant construct occurs. The discriminant validity index summary was generated using Fornell and Larcker (1981) criterion. The diagonal values in bold are the square root of the AVE of the respective constructs, while other values are the correlation coefficient between the pair of the respective constructs.

Referring to Table 6, the discriminant validity was assessed using Fornel and Larcker (1981) by comparing the square root of each AVE in the diagonal with the correlation coefficients (off-diagonal) for each construct in the relevant rows and columns. The Discriminant Validity is achieved if the diagonal values (in bold) are higher than any other values in its row and column. Overall, the tabulated values in Table 6 meet the threshold of Discriminant Validity.

Table 6: The Discriminant Validity Index Summary

Construct	IQ	SQ	SV	PE	EE	SI	FC	PDT	PB	SE	BI	TU
IQ	**0.777**											
SQ	0.681	**0.711**										
SV	0.536	0.623	**0.762**									
PE	0.465	0.540	0.462	**0.779**								
EE	0.609	0.676	0.532	0.621	**0.813**							
SI	0.307	0.470	0.394	0.426	0.370	**0.831**						
FC	0.479	0.412	0.344	0.596	0.624	0.290	**0.794**					
PDT	-0.142	-0.103	0.146	0.031	0.056	-0.005	0.075	**0.736**				
PB	-0.215	-0.181	-0.224	-0.040	-0.140	-0.029	-0.084	0.690	**0.810**			
SE	0.305	0.291	0.209	0.474	0.386	0.217	0.451	0.098	0.025	**0.833**		
BI	0.389	0.399	0.289	0.581	0.463	0.383	0.509	0.059	0.013	0.531	**0.806**	
TU	0.250	0.307	0.175	0.467	0.330	0.271	0.426	0.080	-0.018	0.418	0.618	**0.793**

Names of factors: IQ=Information Quality; SQ=System Quality; SV= Service Quality; PE=Performance Expectancy; EE= Effort Expectancy; SI= Social Influence; FC=Facilitating Conditions; PDT= Perceived Disease Threat; PB= Perceived Barriers; SE= Self-Efficacy; BI=Behavioural Intention; TU=Technology Use.

Readability Level

The readability level of the instrument was analysed using the Flesch Reading Ease Readability Test. The mean score of overall text readability in terms of reading ease was 60.3 (standard), while the mean level of the reading texts in terms of grade level was 8 (grade level 7-8). The suggested age for the readers is 12 to 14 years old. Therefore, it is confirmed that the QHIS measure was designed with a standard level of readability. It is suggested that the consumers can comprehend and complete this measure efficiently.

DISCUSSION

Health information seeking is one of the most important health behaviour constructs for understanding how individuals seek health-related information, adjust psychosocially to illness and develop health activities. Although there are many scales that claim to measure health information seeking in e-health environments, currently there are very few contextually appropriate and usable instruments that are available to measure quality online health information seeking among consumers, specifically in Malaysia, which integrated the definition of the construct including technology acceptance, health behaviour and quality components. The objective of this paper was to test the psychometric properties of the Malaysian version of the QHIS in a sample of Malaysian consumers and validate the scale with CFA.

To date, this is the first study that has tested the factorial structure of the QHIS using CFA, and this analysis adds new insight into the instrument's psychometric properties. The findings revealed that the QHIS is a valid and reliable assessment instrument in Malaysian culture. CFA was conducted to affirm the latent structure of the scale. The first CFA analysis did not indicate a good fit with the solution generated from the original version of the QHIS; as a consequence, it was necessary to explore the factorial structure and revise the model iteratively. Afterwards, the CFA was performed once more. The findings demonstrated that the twelve-dimensional measurement model provided good data-model fit statistics characterised by strong factor loadings, internal reliability, and latent construct estimation.

Furthermore, the study results supported the construct validity of the QHIS and suggested that the QHIS measures the twelve-dimensional theoretical model of health information-seeking. The QHIS measure has achieved the requirement for construct validity, which includes three fundamental categories: absolute fit index, incremental fit index, and parsimonious fit index. The study findings also supported the validity of the 59 items that were selected for each dimension and suggested that the QHIS measure is a psychometrically valid and reliable multi-dimensional measure of health information seeking. Moreover, based on the findings, it is also concluded that the QHIS measure is suitable for Malaysian consumers as the Flesch Reading Ease Readability Test showed a standard level of readability.

In light of the literature, only a limited number of measure were designed to assess quality online HIS in the e-health environment. The study suggests using the QHIS scale as a brief and effective screener for measuring quality online HIS in the e-health system. The prime benefit of this scale is to provide online-based health service providers and practitioners with reliable and valid resources at no cost. The quality online HIS scale could be used as an effective instrument for acquiring information about certain conditions, such as eating disorders or smoking cessation. In addition, health service providers could utilise the measure as a screening tool for developing prevention and intervention strategies for online consumers with health problems. These strategies might encourage consumers' positive health outcomes (e.g., smoking cessation, physical activity and a proper diet) and facilitate consumer health management.

Despite these interesting results, findings from the study should be considered in light of a few methodological limitations for future research. One possible limitation of this study was that the QHIS was validated within the context of e-health systems. Hence, the items were adapted to fit this context. The items would have to be adapted if they were to be used in a different context. Also, different results might be expected across different e-health environments. Future research is thus recommended to investigate whether the scale would function equally well in a different context. Another potential limitation is that only five states were selected, namely Pulau Pinang, Kuala Lumpur, Johor, Selangor, and Melaka. While the involved states were inferred to reflect Malaysian public opinion, the results may not be representative of consumer behaviour towards online HIS across Malaysia. This drawback can be addressed in future research by considering other states in Malaysia and involving more samples to ascertain if the same identified and validated measures of quality HIS in this study will be the same in other states. Finally, because the sample was composed of Malaysian adults, mainly females, our findings have limited external validity and could not be generalised to other populations, such as older or younger consumers. Thus, future studies with a heterogeneous group of participants are needed to examine the psychometric properties of the QHIS in more detail. These limitations of the literature may offer new dimensions of the research area. Considering the current limitations of the literature, this research has given space, opportunities, and recommendations for future researchers to subsequently explore this area in greater detail.

CONCLUSIONS

This is the first study so far that addresses levels and psychometric properties of the QHIS in Malaysia. In conclusion, the QHIS is a valid and reliable tool for assessing quality online health information seeking with good psychometric properties. In addition, its twelve-dimensional solution with 59 items has good fidelity and validity. For these reasons, the QHIS is recommended for future studies investigating health information-seeking. Given the huge body of research on the Asiatic population, the QHIS may contribute to increasing cross-cultural studies needed for a deeper understanding of features and criteria of health information-seeking. The advantages of the QHIS can be summarised as follows: moderate scale, multiple-choice, and easy to understand, apply and rate. The findings from this research also might potentially lead to the creation of a quality-enhanced e-health technology and improving online health information-seeking in e-health environments.

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AUTHOR DECLARATION

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