(MEC-J) Management and Economics Journal
E-ISSN: 2598-9537 P-ISSN: 2599-3402
Journal Home Page: http://ejournal.uin-malang.ac.id/index.php/mec
Volume 9 Number 2, August 2025

The Influence of UTAUT2 Variables on Online Health Information Seeking Behavior for Symptoms Checking

Norman Yanuar

Faculty of Economics and Business, Universitas Pelita Harapan, Tangerang, Indonesia

Corresponding author e-mail: yanuar.norman@gmail.com

ABSTRACT

This study explores the influence of the UTAUT2 variables on Online Health Information Seeking Behavior for symptoms checking. This study used PLS-SEM analysis on 156 respondents who had searched for health information online for symptoms checking. The results show that Habit and Effort Expectancy most influence health information seeking behavior, followed by Performance Expectancy and Social Influence, with age as a significant moderator. Managerial implications include the importance of habit formation and ease of use in online health platforms to increase the usage. This study also makes a theoretical contribution by showing the relationship between UTAUT2 variables and health information seeking behavior, which has rarely been explored before. Further research with larger samples and more specific segment is recommended to enhance the generalizability of these findings.

Keywords: Healthcare; Hospital; Information Seeking Behavior; Online Informed Patient; UTAUT2

| Submited April 2025 | Reviewed May 2025 | Revised July 2025 | Accepted August 2025
| DOI: http://dx.doi.org 10.18860/mec-j.v9i2.32782

INTRODUCTION

The "online-informed patient" has been a growing phenomenon in the healthcare landscape since the rise of internet in the 1990s. A significant portion of the population now actively seeks health information online. For instance, data indicates that 58.5% of adults in the United States engage in this behavior (CDC, 2022). This trend has been further amplified by the development of digital technologies, including smart phones and generative artificial intelligence platforms like ChatGPT. This widespread adoption of digital tools for information retrieval has fundamentally altered the dynamics of the doctor-patient relationship, particularly concerning communication and trust (Farnood et al., 2020; Covolo et al., 2022). A primary driver for this online health information-seeking is the desire of individuals to check their symptoms (Zhang et al., 2021).

Despite the prevalence of this online symptom-checking behavior, there is a scarcity of research examining its underlying drivers. While traditional technology adoption frameworks, such as the Technology Acceptance Model (TAM), have been widely applied in the broader health technology domain, their specific application to this particular behavior remains limited (Jia et al., 2021). Furthermore, the more comprehensive Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, proposed by Venkatesh et al. (2012), remains largely unexplored within healthcare contexts. Previous research has mainly utilized Technology Acceptance Model (TAM) (Davis, 1989) or other general behavioral frameworks to understand online health information-seeking for symptom checking. A significant gap also exists in the geographical focus of these studies, with a notable lack of research specifically centered on emerging markets like Indonesia (G. & Asokan, 2017; Covolo et al., 2022.; Jia et al., 2021).

Southeast Asia, characterized by its rapid digital adoption (Chadha, 2023), presents a critical geographical segment for investigation, offering a non-Western, developing market perspective. Within this region, Indonesia stands out as an ideal setting for this study. As the world's fourth most populous nation, it accounts for approximately half of Southeast Asia's population and features a highly diverse demographic landscape.

This research will be one of the few studies applying select UTAUT2 variables, namely Performance Expectancy, Effort Expectancy, Social Influence, and Habit, to understand Online Health Information Seeking Behavior (OHISB) for the purpose of symptom checking. Moreover, this study will contribute to the literature by providing empirical validation of the model within a Southeast Asian population.

The primary objective of this study is to determine which variables within the UTAUT2 framework most significantly influence OHISB for symptom checking. A secondary objective is to examine the moderating effect of age on these relationships. The findings are expected to provide actionable insights for healthcare providers and platform developers. Specifically, the results can inform the design and strategy of online platforms and channels aimed at engaging patients who seek health information to check their symptoms prior to an offline consultation with a physician.

LITERATURE REVIEW

Unified Theory of Technology Acceptance and Use 2

There have been many theories developed to explain and predict user adoption of information technology with Technology Acceptance Model (TAM) (Davis, 1989) being one of the most important ones. TAM suggests that user motivation is driven by two main variables which are Perceived Usefulness and Perceived Ease of Use. Later, the Unified Theory of Technology Acceptance and Use (UTAUT) (Venkatesh et al., 2003) was developed to provide more comprehensive explanation of the phenomenon. The UTAUT model has four main variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), which determine technology adoption, influencing user behavior. UTAUT also considers variables such as personal identity, gender, age, experience, and voluntary use to modulate the influence of these variables along with behavioral intention and technology use (Venkatesh et al., 2003). Almost a decade later, UTAUT2 was developed (Venkatesh et al., 2012), incorporating three new variables: hedonic motivation, price value, and habit, to understand consumer behavior in a more advanced framework.

Information Seeking Behavior

Krikelas (1983) stated that information seeking starts when an individual feels a lack of knowledge to handle a problem and ends when that feeling is gone, resulting in satisfaction or dissatisfaction. Wilson (2000) explained that Information Seeking Behavior (ISB) is an attempt to seek information intentionally, coming from a need to achieve a goal. In this search process, individuals can interact with manual information systems (such as newspapers or libraries), or with computer-based systems (such as the internet).

The ISB model generally begins with the recognition of a need (Ellis, 1989; Kuhlthau, 1991; Spink and Cole, 2006) and describes the stages that individuals go through to satisfy that need. People tend to seek information sources that are easily accessible even though they may be less accurate (Krikelas, 1983). Ease of access to information supports search behavior, but also causes information overload that reduces the quality of information processing. Fear of making the wrong decision drives customer adoption of ISB. The amount of information collected, processing time, and characteristics of the information (Schick et al., 1990) are the causes of information overload. Effective use of information requires proper processing, namely the activity of finding, classifying, and organizing information for decision making (Schultz and Vandenbosch, 1998). Excess ISB can lead to information dependence and lack of adequate information can cause customer stress and confusion leading to dissatisfaction (Walsh & Mitchell, 2010).

The Link between UTAUT2 and Information Seeking Behavior

Based on a literature review by Jia et al. (2021), the Technology Acceptance Model (TAM) has been confirmed to positively influence OHISB. As TAM evolved, it was developed into UTAUT2. The influence of UTAUT2 on OHISB, however, has not been extensively explored. It is understood that TAM variables affect OHISB. Therefore, it can be inferred that Performance Expectancy (PE) and Effort Expectancy (EE) in the UTAUT2 model, which correspond to Perceived Usefulness and Perceived Ease of Use in TAM, will also drive OHISB.

Furthermore, this study will investigate the relationships between other UTAUT2 variables and OHISB for symptom checking. These variables include SI, HU online health information for symptoms checking, and Age as a moderating variable. In line with the UTAUT2 model, it is anticipated that SI and HU will have a positive impact on OHISB.

Certain UTAUT2 variables were omitted from this research. Hedonic Motivation and Price Value were excluded as they are not particularly relevant to the context of online symptom checking, where the primary motive is not entertainment and the information is generally available for free. The Facilitating Conditions variable was also left out because this study focuses on health information that is broadly accessible on the internet, rather than a new application or channel offered by a specific institution.

Based on the linkages between TAM, UTAUT2, and OHISB identified from the literature review, the following hypotheses were developed which will be tested in the study.

H1: Performance Expectancy on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.

H2: Effort Expectancy on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.

H3: Social Influence on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.

H4: Habit of Using Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.

H5: Age moderates the relationship between Performance Expectancy on Online Health Information for Symptoms Checking and OHISB for Symptoms Checking.

H6: Age moderates the relationship between Social Influence on Online Health Information for Symptoms Checking and OHISB for Symptoms Checking.

These hypotheses are summarized in the conceptual model shown in Figure 1.

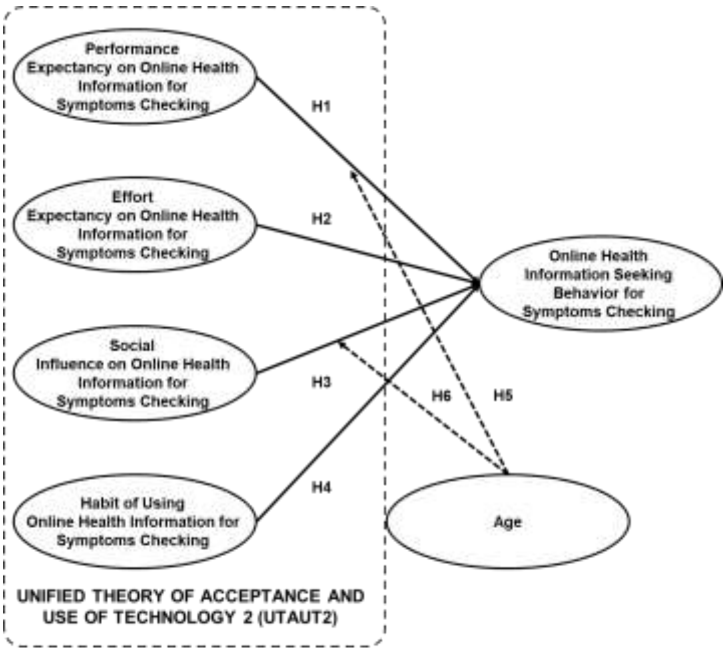

Figure 1. Proposed Conceptual Framework
Source: Author

The conceptual framework for this study is built upon several core constructs. The dependent variable is OHISB for Symptoms Checking. Drawing upon the work of Wilson (2000), this is defined as the intentional efforts made by individuals to seek information to fulfill a specific goal.

This behavior is predicted by four independent variables adapted from the UTAUT2 framework and related literature. Four constructs are derived from Venkatesh et al. (2012): PE on Online Health Information for Symptoms Checking refers to the degree to which an individual believes that using a system will help improve their performance; EE on Online Health Information for Symptoms Checking is conceptualized as the level of ease associated with using the system; SI on Online Health Information for Symptoms Checking is the extent to which an individual perceives that important people around them believe they should use the new system.

Finally, to account for routinized user actions, the model incorporates the HU Online Health Information for Symptoms Checking. Following Moez Limayem & Hirt (2003), this construct is defined as the extent to which people tend to automatically perform behaviors due to previous experiences with the system.

METHODOLOGY

This study utilized a quantitative approach, gathering primary data from patients in Indonesia who had previously undergone outpatient care. The sample was acquired through a convenience sampling method, a non-probability technique chosen for its practicality and accessibility to a specific group of individuals who met the core criterion of the research. The fundamental criterion for a respondent's data to be included in the final analysis was having prior experience in searching for online health information to check their symptoms.

Initially, online surveys were distributed between 27-28 November 2024, yielding 192 responses. After filtering based on the aforementioned criterion, a final sample of 156 respondents was used for the analysis, a number which exceeded the minimum required sample of 129 as calculated by G*Power 3.1.9.7 software.

The data was analyzed using Partial Least Square Equation Modeling (PLS-SEM). This analytical tool was selected for its suitability in exploring the predictive relationships between multiple independent and dependent variables, as well as testing the influence of moderating variables within the proposed conceptual model.

The demographics of the respondents are elaborated in Table 1.

Table 1. Demographic Profile of Respondents

Demographic Profile	n	%
Gender		
Male	65	41.7%
Female	91	58.3%
Age		
<18	1	0.6%
18-25	21	13.5%
26-35	18	11.5%
36-45	53	34.0%
46-55	27	17.3%
>55	36	23.1%
Educational Background		
High School	33	21.2%
Diploma	16	10.3%
Bachelor's Degree	78	50.0%
Master's or Doctoral Degree	29	18.6%
Domicile		
West Java	69	44.2%
North Sumatra	31	19.9%
DKI Jakarta	25	16.0%
Banten	16	10.3%
Central Java	6	3.8%
East Java	4	2.6%
Riau Islands	2	1.3%
Riau	1	0.6%
South Sulawesi	1	0.6%
South Sumatra	1	0.6%

Source: Primary Data Processed, 2024

Measures

All the measures used a 5-point Likert scale to gauge the extent of agreement with the statements, ranging from 1 (strongly disagree) to 5 (strongly agree). The study employed a total of 22 indicators to measure the five primary constructs.

OHISB for Symptoms Checking was measured using a 5-item instrument adapted from Covolo et al. (2022). An example item from this scale is, "I feel confident using online information about my health symptoms to make decisions".

The independent variables from the UTAUT2 framework were adapted from Venkatesh et al. (2012). PE was measured with four items, including statements such as, "Overall, I find searching online for information about my health symptoms beneficial for my life". EE was assessed using five items, with an example being, "The online sources I use for health symptom information are easy to use". SI utilized four items, including, "People important to me suggest that I search for information about my health symptoms online". Lastly, HU was measured with a 4-item scale, featuring statements like, "Searching online for health symptom information has become a habit in my daily life".

The final SmartPLS model used to process and analyze the model is shown in Figure 2.

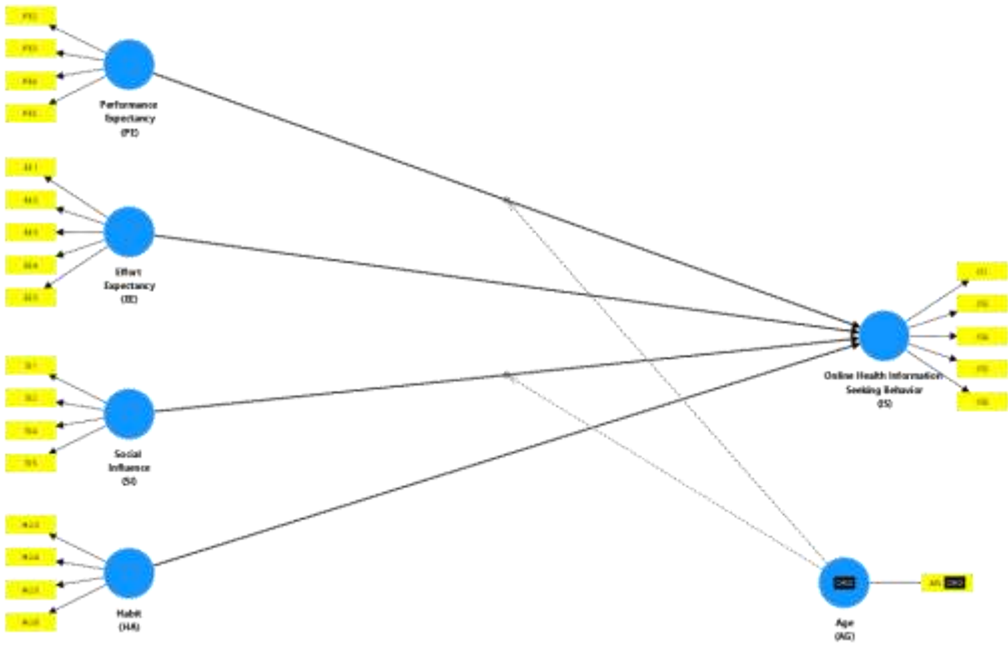

Figure 2. PLS-SEM Model
Source: Primary Data Processed, 2024

RESULTS

Measurement Model

Following Hair et al. (2019), the measurement model was checked by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. As elaborated in Table 2, indicator reliability was confirmed with outer loadings exceeding the recommended threshold of 0.708. Internal consistency was evaluated using composite reliability (CR), with acceptable values ranging between 0.7 and 0.95. Convergent validity was assessed through Average Variance Extracted (AVE), where values above 0.5 indicated satisfactory convergence. Discriminant validity was established using the Fornell-Larcker criterion and HTMT ratios, ensuring that constructs were distinct, with HTMT values below 0.90.

Table 2. Evaluation of Measurement Models

Constructs and Items		Outer Loading
Effort Expectancy (EE) on Online Health Information for Symptoms Checking (AVE=0.777, CR=0.928)		
EE1	Learning how to search for information about my health symptoms online is easy for me.	0.863
EE2	The online sources I use to search for information about my health symptoms are clear and easy to understand.	0.895
EE3	The online sources I use for health symptom information are easy to use.	0.852
EE4	It is easy for me to master how to search for information about my health symptoms online.	0.906
EE5	I find it easy to obtain the expected information about my health symptoms online.	0.890
Habit of Using (HU) Online Health Information for Symptoms Checking (AVE=0.733, CR=0.877)		
HU1	Searching online for health symptom information has become a habit in my daily life.	0.758
HU2	I feel very dependent on online information sources when checking my health symptoms.	0.900
HU3	I always feel the need to search online for information about my health symptoms.	0.903
HU4	I feel comfortable using online sources to find solutions related to my health symptoms.	0.855
OHISB for Symptoms Checking (IS) (AVE=0.657, CR=0.868)		
IS1	I feel confident using online information about my health symptoms to make decisions.	0.713
IS2	I have the skills needed to evaluate health information I find online.	0.846
IS3	I know how to utilize online health information to help myself.	0.858
IS4	I know where to find useful online health information.	0.840
IS5	I am aware of various online health information sources available.	0.785
Performance Expectancy (PE) on Online Health Information for Symptoms Checking (AVE=0.789, CR=0.911)		
PE1	Searching online for information about my health symptoms increases my chances of finding the right solution for me.	0.911
PE2	Searching online for information about my health symptoms helps me find solutions faster.	0.879
PE3	Searching online for information about my health symptoms helps increase my productivity.	0.845
PE4	Overall, I find searching online for information about my health symptoms beneficial for my life.	0.917
Social Influence (SI) on Online Health Information for Symptoms Checking (AVE=0.746, CR=0.885)		
SI1	People important to me suggest that I search for information about my health symptoms online.	0.895
SI2	People who influence my behavior suggest I search for information about my health symptoms online.	0.916
SI3	Friends' suggestions and recommendations influence my decision to search for information about my health symptoms online.	0.850
SI4	I search online for information about my health symptoms because some of my friends do it.	0.788

Description: AVE=average variance of extracted; CR=composite reliability

Source: Primary Data Processed, 2024

Structural Model

Next, the structural model was assessed by examining collinearity, path coefficients, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and model fit. Collinearity was checked using the Variance Inflation Factor (VIF), with values below 5 indicating no multicollinearity concerns. The significance of path coefficients was tested through bootstrapping with 5,000 resamples, where t-values above 1.96 and confidence intervals excluding zero indicated significance.

R^2 value was analyzed to understand the explanatory power of the model. R^2 of the model shown in Table 3 falls between 0.50 – 0.75 indicating moderate explanatory power.

Table 3. The Evaluation of R-square (R^2)

Endogenous Construct	R-Square
OHISB for Symptoms Checking	0.661

Source: Primary Data Processed, 2024

Variance Inflation Factor (VIF) values were calculated to check the existence of multicollinearity among predictor constructs. VIF value shown in Table 4 is below 5 indicating no critical collinearity issues.

Table 4. Evaluation of Collinearity

Construct	VIF
Performance Expectancy (PE)	2.291
Effort Expectancy (EE)	1.959
Social Influence (SI)	1.482
Habit (HU)	1.681

Source: Primary Data Processed, 2024

Based on the PLS-SEM analysis conducted, all the 6 hypotheses shown in Table 5 formed based on the conceptual framework presented at the beginning of this document that can finally be proven. The R2 value shows that this model can explain 66.1% of the variation in Online Health ISB for Symptoms Checking, with Habit being the most significant variable.

Although the UTAUT2 model states that age and gender variables have a moderating effect on the relationship between Habit and behavior (Venkatesh et al., 2012), in the context of online health information seeking which is the focus of this study, only age is proven to have a moderating effect in this model and the moderating effect does not apply to the Habit variable but rather Performance Expectancy and Social Influence.

Table 5. Hypothesis Test Results

Hypothesis	Standardized Path Coefficient	t-value	p-value	Decision
H1: Performance Expectancy on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.	0.196	2.321	0.010	Supported
H2: Effort Expectancy on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.	0.225	3.269	0.001	Supported
H3: Social Influence on Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.	0.132	2.139	0.016	Supported
H4: Habit of Using Online Health Information for Symptoms Checking has a positive influence on OHISB for Symptoms Checking.	0.434	5.647	0.000	Supported
H5: Age moderates the relationship between Performance Expectancy on Online Health Information for Symptoms Checking and OHISB for Symptoms Checking.	-0.198	1.855	0.032	Supported
H6: Age moderates the relationship between Social Influence on Online Health Information for Symptoms Checking and OHISB for Symptoms Checking.	0.239	3.030	0.001	Supported

Source: Primary Data Processed, 2024

DISCUSSION

The analysis confirms that PE positively influences OHISB for Symptoms Checking, supporting the first hypothesis (H1). This result indicates that individuals are more inclined to search for health information online when they believe doing so will be beneficial. This finding is consistent with UTAUT2 model (Venkatesh et al., 2012).

Supporting the second hypothesis (H2), EE was found to be a strong and positive predictor of OHISB for Symptoms Checking. This result demonstrates the importance of user-friendliness in the adoption of online health resources. When individuals perceive that searching for symptom information is easy their propensity to engage in this behavior increases significantly, a finding that aligns with extensive research in technology acceptance (Venkatesh et al., 2012). EE emerged as the second most influential factor after HU in the model.

The third hypothesis (H3) stating a positive relationship between SI and OHISB for Symptoms Checking, was also supported by the data. This finding suggests that the perceptions and recommendations of an individual's social circle, including friends and family, play a role in their decision to check symptoms online. However, it is noteworthy that while statistically significant, the impact of SI was less significant than that of HU and EE.

The analysis revealed that HU is the most powerful predictor of OHISB for Symptoms Checking, providing support for the fourth hypothesis (H4). This finding suggests the importance role of HU suggests that OHISB for Symptoms Checking evolves from a conscious action into an internalized, automatic behavior through repeated use. This aligns with the work of Limayem & Hirt (2003) on technology use.

The fifth (H5) and sixth hypothesis (H6) were supported, revealing the moderating effect of age with further nuance. The model indicates that PE is a stronger driver of OHISB among younger populations, a conclusion that resonates with findings from Cimperman et al. (2016) and Isa and Wong (2015). In contrast, the influence of Social Influence on this behavior was found to be weaker for younger users, suggesting they are less influenced by the opinions or behaviors of their social circle in this specific context.

CONCLUSION

This study successfully identified the key determinants of OHISB for Symptoms Checking by validating a model based on the UTAUT2 variables. The analysis confirmed all six proposed hypotheses, revealing that HU and EE are the most powerful predictors of this behavior. Furthermore, PE and SI were also found to be influential while being moderated by age.

This research offers both managerial and theoretical contributions. Theoretically, it extends the application of the UTAUT2 variables into the OHISB domain, providing an alternative to previous studies which are mainly based on TAM. Managerially, the findings provide clear, evidence-based priorities for healthcare providers when engaging with online-informed patients: to when trying to engage them with a particular online health platform, resources should be focused on creating a seamless, effortless user experience and implementing strategies that foster consistent, repeated use to form a strong Habit. While these findings are significant, they should be used while considering the study's limitations

Implications

This research provides significant contributions to both managerial practice and theoretical understanding, supported by empirically validated findings derived from the analysis. For the managerial domain, this study offers actionable recommendations for healthcare management and practitioners who are designing digital health information channels intended for use by online-informed patients. The following aspects should be prioritized.

First and foremost, ensuring the platform's ease of use is critical. This can be achieved through the development of an intuitive user interface (UI) and by delivering a seamless user experience (UX). Second, fostering habit formation is essential to sustain user engagement. A user engagement strategy should be implemented to encourage repeated use of the channel, for instance, by leveraging incentives, reminders, and notifications about new content to draw users back to the platform.

Lastly, while their influence may be relatively smaller than the first two factors, PE and SI are valuable levers for enhancing the platform's effectiveness in driving OHISB for Symptoms Checking. Practically, this involves clearly communicating the platform's benefits to the targeted users. Additionally, encouraging user referrals or word-of-mouth promotion from satisfied users can be an effective strategy, with this approach being particularly impactful for older demographics as suggested by the finding.

These recommendations align with the Resource-Based View (RBV) theory (Barney, 1991), which posits that managers must strategically allocate internal resources to build capabilities. Accordingly, when developing online channels, prioritizing the two most influential factors identified in this study, namely EE and HU, represents the most efficient use of resources.

On the theoretical aspect, this study makes a distinct contribution by establishing and validating the relationship between some UTAUT2 variables and ISB in healthcare context. Based on the literature review conducted at the time of this writing, this represents a new application of the model, as previous research in this area has mainly relied on the original TAM variables.

Limitations and recommendations

The primary limitation of this study is the usage of the convenience sampling method and the number of samples it employs. This approach may introduce sampling bias, as the data could be skewed towards the specific demographic and geographical segments detailed in the participant profile section of this report.

Further study should expand the sample size as larger and more representative sample would enhance the statistical power of the analysis, leading to more accurate and generalizable results. Future studies could adopt a more focused approach by investigating specific demographic, geographical segments and medical conditions currently faced by the patients, such as chronic illnesses or pediatric-related conditions.

Such research would yield a more granular understanding of the unique behavioral patterns within these distinct populations. It would be beneficial to examine the consequential impacts of OHISB for Symptoms Checking. Research could explore how this behavior influences patient outcomes or decisions before and after consultation with physicians, such as patient satisfaction or adherence.

Finally, incorporating a mixed-methods approach by complementing the quantitative data with qualitative methods, such as in-depth patient interviews, would provide richer insights. This approach could help understand the underlying reasons why certain factors have a more significant influence on behavior than others.

REFERENCES

Chadha, S. (2023, December 12). How Southeast Asia can become a $1 trillion digital economy. World Economic Forum. https://www.weforum.org/stories/2023/12/how-southeast-asia-can-become-trillion-digital-economy/

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior—applying an Extended UTAUT model. *International Journal of Medical Informatics*, 90, 22–31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Covolo, L., Guana, M., Bonaccorsi, G., Brunelli, L., Castaldi, S., De Donno, A., Mereu, A., Verani, M., & Gelatti, U. (2022). Exploring the Online Health Information-Seeking Behavior in a Sample of Italian Women: The "SEI Donna" Study. *International Journal of Environmental Research and Public Health*, *19*(8), 4745. https://doi.org/10.3390/ijerph19084745

D. Wilson, T. (2000). Human Information Behavior. *Informing Science: The International Journal of an Emerging Transdiscipline*, *3*(2), 049–056. https://doi.org/10.28945/576

Davis, F. D. (1989). Perceived usefulness, Perceived Ease of use, and User Acceptance of Information Technology. *Journal of Risk and Uncertainty*, *18*(3), 321–325. https://doi.org/10.1023/a:1011156710779

Ellis, D. (1989). A Behavioural Approach to Information Retrieval System Design. *Journal of Documentation*, *45*(3), 171–212. https://doi.org/10.1108/eb026843

Farnood, A., Johnston, B., & Mair, F. S. (2020). A mixed methods systematic review of the effects of patient online self-diagnosing in the "smart-phone society" on the healthcare professional-patient relationship and medical authority. *BMC Medical Informatics and Decision Making*, *20*(1). https://doi.org/10.1186/s12911-020-01243-6

G., R., & Asokan A., A. (2017). Information seeking behavior causing satisfaction modification intentions. *Journal of Indian Business Research*, *9*(4), 304–328. https://doi.org/10.1108/jibr-09-2016-0090

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Jia, X., Pang, Y., & Liu, L. S. (2021). Online Health Information Seeking Behavior: A Systematic Review. *Healthcare*, 9(12), 1740. https://doi.org/10.3390/healthcare9121740

Krikelas, J. (1983). *Information-seeking behaviour: patterns and concepts*. 19(2), 5–20. Drexel Library Quarterly.

Kuhlthau, C. C. (1991). Inside the search process: Information seeking from the user's perspective. *Journal of the American Society for Information Science*, *42*(5), 361–371. https://doi.org/10.1002/(sici)1097-4571(199106)42:5%3C361::aid-asi6%3E3.0.co;2-#

Moez Limayem, & Hirt, S. G. (2003). *Force of Habit and Information Systems Usage: Theory and Initial Validation*. AIS Electronic Library (AISeL). http://dx.doi.org/10.17705/1jais.00030

Mohd Isa, S., & Wong, K.-Y. (2017). Age Differences in Behavioral Intention to Use Internet Marketing: A Comparative Study Between Malaysian and Taiwanese. *International Journal of Business and Society*, *16*(3). https://doi.org/10.33736/ijbs.574.2015

Schick, A. G., Gordon, L. A., & Haka, S. (1990). Information overload: A temporal approach. *Accounting, Organizations and Society*, *15*(3), 199–220. https://doi.org/10.1016/0361-3682(90)90005-f

Schultz, U., & Vandenbosch, B. (1998). Information Overload in a Groupware Environment: Now You See It, Now You Don't. *Journal of Organizational Computing and Electronic Commerce*, *8*(2), 127–148. https://doi.org/10.1207/s15327744joce0802_3

Spink, A., & Cole, C. (2005). Human information behavior: Integrating diverse approaches and information use. *Journal of the American Society for Information Science and Technology*, *57*(1), 25–35. https://doi.org/10.1002/asi.20249

Vasudeva, S. (2023). Age in the Acceptance of Mobile Social Media: A Comparison of Generation Y and Baby Boomers Using UTAUT2 Model. *International Journal of E-Adoption (IJEA)*, *15*(1), 1–24. https://ideas.repec.org/a/igg/jea000/v15y2023i1p1-24.html

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. JStor. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178.

Walsh, G., & Mitchell, V. (2010). The effect of consumer confusion proneness on word of mouth, trust, and customer satisfaction. *European Journal of Marketing*, *44*(6), 838–859. https://doi.org/10.1108/03090561011032739

Wang, X., & Cohen, R. (2023, November 6). *Products - Data Briefs - Number 482 - October 2023*. Www.cdc.gov. https://www.cdc.gov/nchs/products/databriefs/db482.htm