MAG Scholar® Marketing in Asia Group

AJBR
Asian Journal of Business Research Volume 13 Issue 3, 2023
ISSN 2463-4522 e-ISSN 1178-8933 DOI: 10.14707/ajbr.230158

Research Paper

Factors Influencing Sri Lankan Doctors' Behavior to Recommend Online Purchase of Medical Nutrition Products

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Abstract

Online purchase is becoming an increasingly viable alternative to in-store transactions due to constraints on in-person interaction. However, medical nutrition customers, mostly healthcare patients in Sri Lanka, are still apprehensive about purchasing products online. Doctors' recommendations can positively influence patients' decisions to buy medical nutrition online, but few researchers have studied this. This study incorporated the Unified Theory of Acceptance and User of Technology (UTAUT) to assess what influences doctors to recommend online medical nutrition purchases to their patients. This study utilized a quantitative survey involving 64 medical doctors in Sri Lanka and used partial least squares structural equation modeling for data analysis. The results showed that Performance Expectancy (PE), Social Influence (SI), and Effort Expectancy (EE) affect doctors' Behavior Intention (BI) in recommending online purchasing for medical nutrition. This study will benefit the pharmaceutical industry in accelerating medical nutrition online purchases in Sri Lanka by leveraging doctors as social influencers to recommend online purchases and extend the application of UTAUT in the field.

Keywords: UTAUT, Online Consumer Behavior, Influencer, Pharmaceutical, Healthcare Professional, Physician.

Publication Details: Received 6 April 2023; Revised 22 September 2023; Accepted 4 December 2023

Introduction

Online purchasing is revolutionizing business operations and the customer purchasing experience (Kanwal *et al.*, 2022). Consumers may purchase anything with a single click from online suppliers, eliminating the need to visit the store. Access, search, assessment, transaction, and post-purchase convenience are the five primary benefits of online purchases (Pham *et al.*, 2020). Search engines facilitate online purchases as they help consumers find and compare online goods and services. Google Search holds a 97.57% share of the Sri Lankan search engine market, followed by Bing with 1.57% (StatCounter, 2023). According to the Digital 2022 report by DataReportal (Kemp, 2022), internet penetration in Singapore reached 92.0%, while rising nations such as Vietnam and Sri Lanka had penetration rates of 73.2% and 52.6%, respectively. According to World Bank data, Sri Lanka's internet penetration climbed from 21% in 2017 to 35% in 2020, whereas Vietnam's increased from 58% to 70% in 2020 (The World Bank Group, 2023). People adopted internet applications and online purchases as a viable alternative to offline shopping due to their fears of pandemics, desire to feel safe at home, and government restrictions (Jayarathne *et al.*, 2022; Jílková and Králová, 2021). This phenomenon motivates businesses, including pharmaceutical companies, to use digital technologies to serve, interact with consumers, and raise brand awareness (Apasrawirote and Yawised, 2022; Tran, 2021).

A key concern is that Sri Lankan medical nutrition customers, predominantly healthcare patients, remain apprehensive about online purchases, indicating that negative factors impede the adoption of online purchasing (Karnadi *et al.*, 2022). People find it challenging to accept mobile payments in Sri Lanka because they are unfamiliar with the concept and have security concerns: neither customers nor employees are technology experts, resulting in poorly managed technology-related difficulties (Jayarathne *et al.*, 2022). Online pharmaceutical sales are associated with public health risks, such as selling prescription-only medications without any prescription or counterfeit or low-quality drugs, as well as cybersecurity concerns, such as consumer fraud and data privacy (Miller *et al.*, 2021).

Researchers have published a considerable amount of literature on factors affecting online purchases, such as age (Phang *et al.*, 2018), consumer behavior (Asiedu and Dube, 2020), and culture (Eine and Charoensukmongkol, 2021). In emerging markets, internet security, lack of computer and internet education, and the lack of internet exposure and awareness affected the adoption of online purchases (al Sideiri *et al.*, 2021). Like traditional shoppers, personalized recommendations impact online shoppers (Ampadu *et al.*, 2022). Previous research proposes that customers seek information from private sources once they identify a need according to the 'health products purchase model' (Ting *et al.*, 2019). Doctors or health professionals are among the sources and have been regarded as the most influential group, making them the pharmaceutical industry's primary promotion target (Narayan *et al.*, 2020; Srivastava and Wagh, 2017; Ting *et al.*, 2019). Yet, there has been limited study investigating doctor behavior, especially on the doctor's drivers in endorsing online purchase adoption.

This study incorporates the Unified Theory of Acceptance and Use of Technology (UTAUT). Numerous studies have used UTAUT to predict and identify elements that drive technology adoption (Karnadi *et al.*, 2022; Patil *et al.*, 2020; Phang *et al.*, 2018; Venkatesh *et al.*, 2016). Identifying the factors that influence doctors' behavior to recommend online purchases to their patients will leverage the Sri Lankan online purchase market and broaden the applicability of UTAUT in this field. Online shopping will also contribute to the growth of e-pharmacy, making it easier for people to obtain the medications they require, particularly if they have to take long-term daily medicines or cannot visit a traditional pharmacy (Miller *et al.*, 2021). This study also presents an intriguing potential for pharmaceutical businesses transitioning to digital marketing (Ngamvichaikit, 2021) by investigating the possibilities of using doctors as social influencers to digitize their patients.

Literature Review

In recent years, there has been a rise in interest in online purchases; the Web of Science database contains over 5,000 publications and over 30,000 citations throughout December 2021 on online purchases or online consumer behavior (Thaichon *et al.*, 2022). Most studies investigated online consumer behavior or online decision-making or features affecting online purchase adoption with the consumer as the focal point (Thaichon *et al.*, 2022), issues surrounding online purchases such as consumer privacy (Chen *et al.*, 2022), issues supporting service such as mobile banking (Souiden *et al.*, 2021), and electronic word-of-mouth (eWOM) (Donthu *et al.*, 2021). According to the systematic review of eWOM, there is also a need to explore customers' Anxiety when giving their opinion (Donthu *et al.*, 2021). Furthermore, prior studies have identified significant information gaps in pharmaceutical digital marketing, with only fourteen studies produced in the last two decades and four written by the same author (Anis and Hassali, 2022).

Doctor as an influencer for online purchase

A doctor prescribes medical nutrition once they have diagnosed their patient with a particular disease, such as cancer or chronic kidney disease, as one of the medical treatments to anticipate malnutrition (Dominguez Castro *et al.*, 2020; Fierini and Madill, 2020; Roumeliotis *et al.*, 2019; Srivastava and Wagh, 2017). The importance of a doctor's endorsement in a patient's buying decision makes them one of the most influential social influencers for health products (Narayan *et al.*, 2020). Regarding medical nutrition online purchases, customers perceived this new technology as helpful and easy to use, which could increase patient compliance with doctors' orders and decrease malnutrition (Karnadi *et al.*, 2022). Nevertheless, Anxiety negatively impacts customers' intention to purchase online (Karnadi *et al.*, 2022). This study will investigate the variables influencing doctors' behavior to voice their opinion as one of the critical social influencers for health products (Narayan *et al.*, 2020; Srivastava and Wagh, 2017; Ting *et al.*, 2019) by recommending online purchases to patients.

UTAUT & Anxiety

This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the antecedent of doctors' behavior in recommending online purchases to their patients. Researchers have repeatedly applied the UTAUT model to predict and identify factors that drive technology adoption due to its robustness (Karnadi *et al.*, 2022; Patil *et al.*, 2020; Phang *et al.*, 2018; Souiden *et al.*, 2021; Venkatesh *et al.*, 2016). TAM (Technology Acceptance Model) by Davis was another model widely used to analyze the level of technological adoption (Davis, 1989; Souiden *et al.*, 2021).

However, several recent studies have critiqued the usage of TAM since its framework does not account for additional complicated vital elements of the decision-making process (Marinković *et al.*, 2020).

UTAUT is the notion that forecasts the acceptance and implementation of technology by combining all components of the eight preceding well-known theoretical frameworks. TAM is one of the theories integrated into UTAUT. UTAUT itself has four key factors: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). To predict a doctor's action (ACT) in recommending patients to purchase medical nutrition online, the UTAUT model utilized consists of five key determinants: Performance Expectation (PE), Effort Expectancy (EE), Social Influence (SI), Anxiety (AX), and Facilitating Conditions (FC), with Behavioral Intention (BI) mediating them (Venkatesh *et al.*, 2016). Figure 1 presents the framework for this research.

Performance Expectation (PE) is the extent to which an individual believes that technology will simplify particular tasks and is the most significant predictor of technology adoption (Venkatesh *et al.*, 2003). In this study, medical nutrition refers to the oral milk nutrition supplements given to patients diagnosed with a particular disease, such as cancer or chronic kidney disease, as part of doctors' medical treatment (Dominguez Castro et al., 2020; Fierini and Madill, 2020; Roumeliotis et al., 2019; Srivastava and Wagh, 2017). Online medical nutrition purchases can provide patients with greater convenience, accessibility, and product variety, which can benefit healthcare services, increase patient compliance to follow doctors' medical nutrition treatment, and decrease malnutrition (Karnadi et al., 2022; Nguyen *et al.*, 2021; Pham *et al.*, 2020).

Previous studies have shown that PE positively influences various types of technology adoption, such as mobile health adoption (Hoque and Sorwar, 2017), mobile commerce adoption in Serbia (Marinković *et al.*, 2020), online buying in Malaysia (Soh *et al.*, 2020), online shopping in Sri Lanka (Karnadi *et al.*, 2022), and telemedicine adoption (Schmitz *et al.*, 2022). However, these studies focused on consumer perspectives rather than health care professionals. Therefore, this study aims to fill this gap by exploring how PE affects doctors' intention to recommend online medical nutrition purchases to their patients. The hypothesis is as follows:

H1 Performance Expectancy (PE) positively affects doctors' intention (BI) to recommend online medical nutrition purchases to their patients.

Effort Expectancy (EE) is the perceived ease or difficulty of using technology to complete connected tasks (Venkatesh *et al.*, 2003). This study defines EE as the extent to which online purchase is perceived to be easy to learn when buying medical nutrition. Numerous studies have demonstrated the significant impact of EE on the rate of new technology adoption in various domains (Penney *et al.*, 2021; Sankaran and Chakraborty, 2022; Sezgin *et al.*, 2018; Sivathanu, 2019). Sankaran & Chakraborty (2021) showed that EE influences the intent to utilize mobile banking in India, a similar finding reported by Sezqin et al. (2018) in mobile health application usage among Turkish doctors (Sankaran and Chakraborty, 2022; Sezgin *et al.*, 2018). In this study, EE shows doctors' perceptions that purchasing medical nutrition online is easy to master, and the following hypothesis is supported:

H2 Effort Expectancy (EE) positively affects doctors' intention (BI) to recommend online medical nutrition purchases to their patients.

Social Influence (SI) is the extent to which an individual feels that their environment encourages them to adopt a technology (Venkatesh *et al.*, 2012). In this study, SI examines the extent to which people believe purchasing medical nutrition is appropriate and whether medical nutrition companies support this notion. It is also understood that Social Influence strongly influences behavior in China, India, and other countries (Asiedu and Dube, 2020; Tak and Panwar, 2017). Studies on online shopping adoption show that SI also drives mobile health adoption (Hoque and Sorwar, 2017), but this is not the case for telemedicine (Schmitz *et al.*, 2022). Social Influence affects doctors' intention to recommend their patients to purchase nutrition products as doctors feel confident and motivated to suggest online options endorsed by their peers, professional associations, or medical nutrition companies. Therefore, this study proposes the following hypothesis:

H3 Social Influence (SI) positively affects doctors' intention (BI) to recommend online medical nutrition purchases to their patients.

In UTAUT, Facilitating Conditions (FC) is the driver that directly influences Action (ACT) rather than Behavior Intention (BI). FC is the extent to which an individual believes an organizational and technological infrastructure exists to support technology adoption (Soh *et al.*, 2020; Venkatesh *et al.*, 2012). This study defines facilitating conditions as the availability and quality of resources such as internet connections, mobile phones, and other infrastructure or troubleshooting assistance that facilitate online purchasing. FC is the most crucial aspect in developing nations for adopting eCommerce (Datta, 2011), as it determines the accessibility and reliability of online services. This condition results in a digital divide and limits the potential of online purchasing. Soh et al. (2020) reported a similar finding that showed FC influences online shopping in Malaysia. However, a recent study contradicts the notion that FC affects online shopping (Karnadi *et al.*, 2022). However, this study focuses on the perspective of consumers or patients rather than health care professionals. According to Kemp (2022), internet penetration in Sri Lanka in 2022 is only 52.6%, which is relatively low compared to other Asian nations such as Vietnam (73.2%) and Singapore (92.0%). Therefore, it may restrict doctors from recommending purchasing medical nutrition products online. Hence, the hypothesis is as follows:

H4 Facilitating Conditions (FC) positively affect doctors' actions (ACT) to recommend online medical nutrition purchases to their patients.

Anxiety is the perceived risk and uncertainty associated with a specific action (ben Arfi *et al.*, 2021). Previous studies have shown that Anxiety negatively affects mobile health in Bangladesh (Hoque and Sorwar, 2017), mobile banking in India (Patil *et al.*, 2020), virtual learning in Sri Lanka (Gunasinghe and Nanayakkara, 2021), and online shopping (Karnadi *et al.*, 2022).

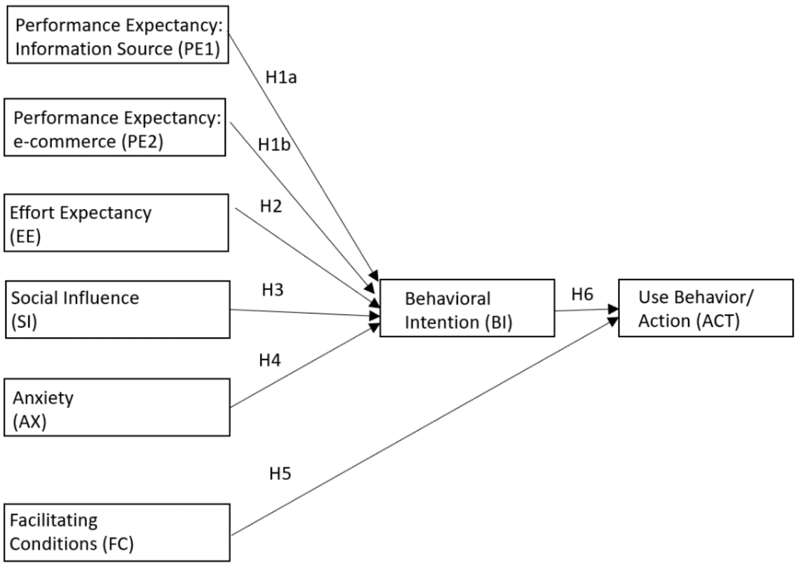
Since purchasing medicinal nutrition online does not require a doctor's prescription, doctors may hesitate to recommend it to their patients. This study introduced Anxiety as an exogenous variable to the four key variables determining Behavior Intention (BI) components. The subsequent hypothesis is as follows:

H5 Anxiety (AX) negatively affects doctors' intention (BI) to recommend online medical nutrition purchases to their patients.

Behavioral Intentions (BI) directly and positively influence action (Davis, 1989; Patil *et al*., 2020; Venkatesh *et al*., 2003). Once a person intends to make an online purchase, they will act accordingly. This study measured the strength of individuals' intention to engage in a particular behavior using a three-item scale developed by Davis et al. (1989). The following hypothesis is as follows.

H6 Behavioral Intention (BI) positively affects doctors' actions (ACT) to recommend online medical nutrition purchases to their patients.

Figure 1: Conceptual Framework of the Study



Methodology

Questionnaire Development, Sample Selection, and Data Collection Procedure

In this study, we utilized a structured self-administered questionnaire based on the UTAUT questionnaires (Venkatesh *et al.*, 2003) and translated it into Sinhala, the primary language in Sri Lanka. They then performed back translation to check the accuracy and quality of the translation. This survey has two items with negative wording. The first negative wording question is the facilitating condition question (FC-3), and the second is the action measurement question (ACT-3). Five non-study hospital-affiliated doctors served as the pilot sample for the survey.

We conducted the research in Sri Lanka's two largest cities: Colombo and Kandy. Medical nutrition prescription is still uncommon among Sri Lankan doctors. Most specialists provide this for chronic disease patients who are more prone to malnutrition (Fierini and Madill, 2020). Furthermore, gaining the willingness of medical doctors who prescribe medical nutrition to participate in the survey is difficult, as they may be too busy or unwilling to share their opinions. Hence, the sampling technique used for this study was non-probability purposive sampling, which relies on the personal judgment of the researchers to select medical doctor survey participants.

Sixty-four medical doctors prescribing medical nutrition participated in the study: 46 from Colombo and 18 from Kandy, with a skewed gender distribution of 36 males and 28 females. OECD (2021) reports that female doctors are more likely to work in general medicine and pediatrics. This challenge, limited time, and resource constraints made it hard to find more than 30 female doctor respondents. Cohen (1992) gave some rules of thumb that researchers can use for multiple regression models since PLS-SEM sample size recommendations are based on OLS regression's properties. Researchers can apply this rule of thumb, provided the measurement models have an acceptable quality in outer loadings of 0.70 or higher (Hair Jr. *et al.*, 2017). When using a measurement and structural model with five independent variables, forty-five (45) sample sizes are needed to detect R2 values of at least 0.25 with 80% statistical power and a 5% error probability (Hair Jr. *et al.*, 2017). Hence, the sample meets the standard minimum requirements.

Table 1: Respondent Questionnaire

Construct	Code	Item
Performance Expectancy (PE)	PE1	I find Google search, websites, and email useful for enlightening and explaining medical nutrition about patient disease therapy.
	PE2	Utilizing Google Search, websites, and email allows me to convey the significance of medication nutrition swiftly.
	PE3	Utilizing Google search, websites, and email helps me to offer medical nutrition to more patients to treat their illnesses.
	PE4	I would find social media (such as Instagram and Facebook) helpful for informing and explaining medical nutrition in treating patient illness.
	PE5	Utilizing social media (such as Instagram and Facebook) expedites my ability to describe the significance of medical nutrition.
	PE6	Utilizing social media (such as Instagram and Facebook) allows me to offer medical nutrition to more patients to treat their illnesses.
	PE7	I would find e-commerce (such as Tiki, Shopee, and Lazada) valuable as an alternate point of sales for patients to purchase medical nutrition.
	PE8	Utilizing e-commerce (such as Tiki, Shopee, and Lazada) would make patients feel better because it would decrease their time spent waiting at the hospital or pharmacy.
	PE9	More patients will buy medical nutrition via e-commerce (such as Tiki, Shopee, and Lazada) if available.
Effort Expectancy (EE)	EE1	I think online purchases of medical nutrition are clear and easy to understand.
	EE2	Online purchasing of medical nutrition would be simple for me to learn.
	EE3	In my opinion, purchasing medical products online is simple.
	EE4	It is simple for me to learn how to purchase medical nutrition products online.
Social Influence (SI)	SI1	The individuals influencing my conduct believe I should purchase medical nutrition products online.
	SI2	The individuals who are significant to me believe I should purchase medical nutrition products online.
	SI3	The medical nutrition firm's senior management has assisted with the online transactions.
	SI4	Medical nutrition firms have, in general, been in favor of online transactions.

Anxiety (AX)	AX1	I am skeptical of the concept of purchasing medical nutrition products online.
	AX2	The online transaction procedure is somewhat unsettling to me.
	AX3	I am unsure if I want to purchase medical nutrition products online due to their downsides (such as e-voucher complexity and bonus redemption)
Facilitating Condition (FC)	FC1	I have the means to purchase medical nutrition products online.
	FC2	I have sufficient information to purchase medical nutrition products online.
	FC3	Purchasing medical nutrition products online is more complicated than purchasing them offline.
	FC4	A designated individual (or group) can assist with online transaction issues.
Behavior Intention (BI)	BI1	If medical nutrition products are available online, I plan to suggest my patients purchase medical nutrition products online.
	BI2	If medical nutrition products are available online, I would recommend that my patients purchase them online.
	BI3	If medical nutrition products are available online, I intend to suggest purchasing medical nutrition products online.
Use Behavior /Action (ACT)	ACT1	I did suggest to my patients that they should purchase medical nutrition products online.
	ACT2	I have suggested to my patients that they purchase medical nutrition products online.
	ACT3	I have never suggested to a patient to purchase medical nutrition products online.

Table 2 presents the descriptive analysis of this study. Out of 64 medical doctor respondents, 56% were male (36 respondents), and 44% were female (28 respondents). The age group varied from 27 to 62 years old with a variety of job experiences, with 46-50 years having the most significant proportion (25%) in the age group and 6-10 years having the largest percentage (28%) in the work experience group. All indicator means are more than 2.8, indicating a positive response to the indicators. The standard deviation of the highest indicator is 0.90, indicating that respondents had comparable responses to the questions.

Table 2: Respondents' Demographic Characteristics

Demographics		**Frequency**	**Percentage**
Gender	Male	36	56%
	Female	28	44%
Experience	<5 years	4	6%
	6-10 years	18	28%
	11-15 years	8	13%
	16-20 years	3	5%
	21-25 years	15	23%
	26-30 years	11	17%
	>30 years	5	8%
Age	<=30 years	2	3%
	31-35 years	8	13%
	36-40 years	9	14%
	41-45 years	6	9%
	46-50 years	16	25%
	51-55 years	15	23%

56-60 years	5	8%
>60 years	3	5%

Results

The data were analyzed using two software. Firstly, we conducted an exploratory factor analysis (EFA) using SPSS Version 27. From 30 indicators, the reliability test of FC was very low (-0.072) due to the reversed coded item (FC3R), which was the question with negative phrasing in this survey. Thus, we removed FC3R from this model (Suárez-Alvarez *et al.*, 2018).

Direct Oblimin was applied as an element of principal component analysis to check if more than one factor was found in each construct. The study revealed a problem with the unidimensionality of the performance expectation variable. Therefore, we discarded the second component consisting of three variables (PE1, PE7, and PE9) with minimal explained variance (15%) and low Cronbach's alpha reliability coefficient (0.437).

SmartPLS3 software was then used to evaluate the data (Hair *et al.*, 2019; Hair Jr. *et al.*, 2017). This study utilized the PLS-SEM (Partial Least Square Structural Equation Modeling) technique, which maximized the variance of the dependent latent constructs (Hair Jr. *et al.*, 2017).

This study used factor analysis to analyze the relationship between seven constructs and their indicators. Table 3 shows the outcome of the analysis. In SEM, factor loadings of 0.7 or greater were recommended (Hair Jr. *et al.*, 2017). Twenty (20) indicators had factor loadings between 0.77 and 0.96 that exceeded the recommended threshold. Six (6) indicators, EE1, AX2, AX3, FC1, FC2, and ACT3R, had a factor loading of less than 0.7, and we eliminated these indicators.

Afterward, we evaluated the measurement model by examining the constructs' internal reliability, convergent validity, and discriminant validity. Internal reliability indicates how accurately a construct is measured by its components and examined by Cronbach's alpha and Composite Reliability (CR). Meanwhile, we analyzed convergent validity through Average Variance Extracted (AVE), which is the grand mean of the squared loadings of the indicators associated with the construct. These three evaluation indicators are the most common ones (Hair Jr. et al., 2017). All of Cronbach's alpha values in each construct were above 0.89 and exceeded the suggested threshold of 0.7. Similarly, the Composite Reliability (CR) values were above 0.92, and the AVE values were above 0.67, surpassing the recommended thresholds of 0.7 and 0.5, respectively (Hair *et al.*, 2019). Therefore, the items and constructs included in the model were reliable and valid.

Table 3: The Measurement Model

Constructs	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Performance Expectancy (PE)	PE2	0.80	0.90	0.92	0.67
	PE3	0.89			
	PE4	0.82			

	PE5	0.77			
	PE6	0.78			
	PE8	0.85			
Effort Expectancy (EE)	EE1	0.68	0.91	0.94	0.84
	EE2	0.91			
	EE3	0.91			
	EE4	0.86			
Social Influence (SI)	SI1	0.89	0.89	0.92	0.75
	SI2	0.84			
	SI3	0.90			
	SI4	0.84			
Anxiety (AX)	AX1	0.86	1.00	1.00	1.00
	AX2	(0.27)			
	AX3	0.06			
Facilitating Condition (FC)	FC1	0.30	1.00	1.00	1.00
	FC2	0.38			
	FC4	0.93			
Behavior Intention (BI)	BI1	0.94	0.92	0.95	0.86
	BI2	0.93			
	BI3	0.90			
Use Behavior /Action (ACT)	ACT1	0.96	0.91	0.96	0.91
	ACT2	0.95			
	ACT3R	0.23			

This study assessed discriminant validity for PLS-SEM using the Fornell-Larcker and HTMT (heterotrait-monotrait) criteria. Table 4 demonstrates that the Fornell-Larcker criterion was met, as the square root of the AVE for each concept (in bold) was more significant than the inter-construct correlations (in off-diagonal values) (Fornell and Larcker, 1981; Hair Jr. et al., 2017). The HTMT criterion, which is superior to the Fornell-Larcker criterion, was also satisfied, as shown in Table 5, in which all HTMT values were below the conservative threshold of 0.85 (Hair Jr. et al., 2017; Henseler et al., 2015).

Table 4: Discriminant Validity (Fornell-Larcker Criterion)

	ACT	**BI**	**EE**	**FC**	**MA**	**PE**	**SI**
AX	**1.000**						
BI	-0.410	**0.925**					
EE	-0.384	0.668	**0.919**				
FC	-0.108	0.175	0.167	**1.000**			
ACT	-0.201	0.558	0.373	0.108	**0.956**		
PE	-0.282	0.658	0.529	0.144	0.519	**0.819**	
SI	-0.205	0.633	0.474	0.207	0.646	0.587	**0.868**

Table 5: Discriminant Validity (HTMT)

	ACT	AX	BI	EE	FC	PE
AX	0.384					
BI	0.607	0.410				
EE	0.399	0.390	0.713			
FC	0.110	0.261	0.185	0.172		
PE	0.571	0.273	0.698	0.571	0.184	
SI	0.729	0.244	0.683	0.514	0.213	0.654

To avoid common method bias (CMB) or the impact of common method variance (CMV) on the measured variables, we checked the variance inflation factor (VIF) values before the analysis. Table 6 shows the inner model from a full collinearity test with VIF values below 3, indicating no CMB (Chaouali et al., 2021; Hair *et al.*, 2019; Kock, 2015).

Table 6: VIF Values

	Use Behavior /Action (ACT)	Behavior Intention (BI)
Performance Expectancy (PE)		1.76
Effort Expectancy (EE)		1.61
Social Influence (SI)		1.62
Anxiety (AX)		1.20
Facilitating Condition (FC)	1.03	
Behavior Intention (BI)	1.03	

The coefficient of determination R Square Adjusted of the model is well represented to explain the variance in Behavior Intention (BI). In this study, 60.5% of the independent variables will predict doctors' intention in recommending their patients to make online medical nutrition purchases (BI), as predicted by these independent variables. Meanwhile, the R Square Adjusted is 30% for doctors to recommend patients buy medical nutrition online (ACT).

Table 7 presents the outcomes of the hypotheses. Path analysis results demonstrated that the Influence of components affected the structural level or effect size. If the standardized correlation coefficient (β) is more than 0.30, there is a significant effect. Three hypotheses were statistically significant at $p < 0.001$ with two large effect sizes (>0.30), namely hypotheses H2 (relationship between Effort Expectancy and Behavior Intention) and H6 (relationship between Behavior Intention and Action). The third Hypothesis, H3, testing the relationship between Social Influence and Behavior Intention, had a moderate effect(β=0.29). The last hypothesis supported in this model was H1, which examined the relationship between Performance Expectancy and Behavior Intention, which revealed a modest effect size (β=0.27) with a lesser statistical significance ($p<0.05$); nonetheless, it was still acceptable.

Table 7: Path Analysis

Hypothesis	Path Coefficient (β)	T-statistics	P values		Study Result
H1: PE → BI	0.27	2.55	0.011	**	Supported
H2: EE → BI	0.33	4.10	0.000	***	Supported
H3: SI → BI	0.29	3.04	0.002	***	Supported
H4: FC → BI	0.01	0.11	0.913		Not supported

H5: AX →BI	(0.15)	1.84	0.065	*	Not supported
H6: BI → ACT	0.56	5.40	0.000	***	Supported

*P<0.1, **P<0.05, ***P<0.001

As the final step, we analyzed the predictive power using PLS Predict (Hair *et al.*, 2019; Shmueli *et al.*, 2019) with the default settings (ten folds and ten repetitions), as shown in Table 8. Based on this analysis, three Q2 predict values of PLS were more than LM's Q2 predict values (out of five), and the PLS's root mean square error (RMSE) statistics of three items (out of five) were less than LM's RMSE. In this case, it inferred a medium prediction accuracy (Shmueli *et al.*, 2019).

Table 8: Predictive Power Analysis

	Partial Least Squares (PLS)		Linear Model (LM)	
	Q^2_predict	RMSE	Q^2_predict	RMSE
BI3	0.431	0.614	0.408	0.626
BI1	0.560	0.512	0.584	0.498
BI2	0.436	0.612	0.150	0.752
MA1	0.320	0.774	0.243	0.816
MA2	0.258	0.808	0.299	0.785

Discussion

This study found that three variables, namely Effort Expectancy (EE), Social Influence (SI), and Performance Expectancy (PE), accounted for 60.5% of the independent variables influencing the behavior intention of Sri Lankan doctors to recommend the online purchase of medical nutrition to their patients. This study found that Effort Expectancy (EE) had the highest path coefficient (0.33) as the primary predictor of doctors' intention to recommend online purchases. This result is consistent with earlier studies indicating that EE has a significant impact on the adoption of new technology in various settings (Penney *et al.*, 2021; Sankaran and Chakraborty, 2022; Sezgin *et al.*, 2018; Sivathanu, 2019). The study also found that doctors perceived purchasing medical nutrition online as simple, similar to the consumer study on medical nutrition online purchases (Karnadi *et al.*, 2022). The ease of online purchasing is the factor that influences doctors to recommend that patients purchase medical nutrition online.

Social Influence (SI) is the second predictor encouraging the doctor to recommend online purchases with a path coefficient of 0.29. Social Influence refers to the extent to which a person perceives that others who are important to them think they should or should not perform a specific behavior. This study adds one more country to the list of Asian countries, such as China (Asiedu and Dube, 2020) and India (Tak and Panwar, 2017), where SI significantly affects online purchasing. A prior study by Soh et al. (2020) also supported that Social Influence significantly affects online shopping. The opinions of friends, family, and others substantially affect Asian consumer behavior conduct. Therefore, this study concludes that Social Influence is essential in shaping online purchasing behavior endorsement among doctors in Sri Lanka and other Asian countries.

Performance Expectation (PE) is the final indicator influencing a doctor's intention to recommend that their patients make online medical nutrition purchases with a path coefficient of 0.27. The fact that online purchase has benefits is why doctors intend to recommend this. It supports the theory by Venkatesh et al. (2016) that PE significantly predicts technology adoption. Studies on the adoption of mobile health (Hoque and Sorwar, 2017), mobile commerce (Marinković *et al.*, 2020), online buying (Soh *et al.*, 2020), and telemedicine (Schmitz et al., 2022) all support this. It also confirms that doctors believe their patients will benefit from purchasing medicine nutrition online (Hsu and Le, 2020; Marinković *et al.*, 2020; Nguyen *et al.*, 2021; Pham *et al.*, 2020)

In this study, Facilitating Conditions (FC) like internet connections, mobile phones, and other infrastructures or troubleshooting assistance that support online purchases no longer influence doctors' actions to recommend online purchases. The COVID-19 pandemic has encouraged people to shop online due to its necessity: the internet penetration in Sri Lanka reached 52.6% in 2022 (Kemp, 2022), almost double that of five years ago (The World Bank Group, 2023). Most doctors believe that adequate resources exist to facilitate online purchases. This study thus further supports the idea that Facilitating Conditions are no longer relevant, reaching the same outcome as the study on medical nutrition consumers' intention to purchase online (Karnadi *et al.*, 2022).

This study indicates that Anxiety has no substantial effect on the behavior intention of doctors to recommend online purchases. Prior studies have revealed the increased popularity of online shopping because of its benefits (Kanwal *et al.*, 2022; Pham *et al.*, 2018). As people become more familiar with online shopping, the perceived risk with online shopping activities, Anxiety, is also minimized to a nonsignificant effect. Earlier research has found that Anxiety is a determinant of technology adoption, such as in the adoption of mobile health (Hoque and Sorwar, 2017) and mobile payment (Patil *et al.*, 2020). This study did not find any evidence of Anxiety being a determinant of technology adoption in online purchases for medical nutrition. Therefore, the researchers can conclude that Anxiety is no longer relevant in this context.

Past research indicates that doctors' intention has a positive and direct effect on action (Davis, 1989; Karnadi *et al.*, 2022; Patil *et al.*, 2020; Venkatesh *et al.*, 2016). Nevertheless, many drivers still influence doctors' intention to take action in recommending online medical nutrition to their patients. This study showed that though these three drivers account for 60.5% of intention, they only affect 30% of doctors' actions to recommend their patients to conduct online purchases of medical nutrition in Sri Lanka.

Implications

This study extends the application of the UTAUT model in the medical field in the Sri Lankan context, which explains factors influencing Sri Lankan doctors' behavior in recommending online purchases of medical nutrition to patients. It is found that three variables, namely Effort Expectancy (EE), Social Influence (SI), and Performance Expectancy (PE), affect doctors' intention to recommend online purchases. Therefore, these three variables must be the focus to drive doctors to recommend an online purchase for medical nutrition.

The relationship between these variables and doctors' behavioral intention to recommend online purchases is an under-researched topic in the medical field yet crucial due to the importance of online purchase adoption considering its tremendous benefit. Online purchase adoption can make it easier for patients to obtain medications, especially for those who take long-term daily medications and have difficulty visiting traditional pharmacies. This is particularly relevant in developing countries like Sri Lanka, where access to healthcare services is limited. Online purchasing can help patients save time and money by avoiding long queues and transportation costs.

This study also has implications for pharmaceutical companies transitioning to digital marketing by leveraging doctors as social influencers to digitize their patients. By understanding the factors influencing doctors' Behavior Intention (BI) to recommend online purchases, pharmaceutical companies can develop targeted marketing strategies focusing on these factors. The ease of online purchasing is the first primary factor for doctors to recommend online purchases. For instance, they can develop campaigns highlighting the ease of use of online purchasing platforms. Considering that Social Influence (SI) plays a significant role in shaping doctors' Behavior Intention (BI) to recommend online purchases, pharmaceutical companies can develop campaigns by leveraging social media platforms to promote the benefits of online purchasing. Lastly, since Performance Expectation (PE) is the third influencing factor, this means that doctors who believe that online purchase has benefits are more likely to recommend it to their patients. Hence, there should be training for doctors so more of them would be exposed to the benefits of online shopping for their patients and become more comfortable with recommending online purchases.

Lastly, the findings of this study also confirmed that doctors believe that their patients will benefit from purchasing medicinal nutrition online. This finding has important implications for policymakers as well. By understanding the benefits of online purchasing, policymakers can develop strategies to promote the adoption of online purchases in healthcare settings. In conclusion, this study provides valuable insights into the factors influencing doctors' Behavior Intention (BI) to recommend online purchases.

Nevertheless, the sample size limits the generalizability of the results. Therefore, future research should employ a more prominent and representative sample of medical doctors to enhance the validity and applicability of the findings.

Practical Implications for Asian Business

This study will profoundly impact how a business can effectively use doctors as social influencers to digitize their patients and stimulate the growth of medical nutrition online purchases and digitalization. It is particularly beneficial for Asian countries, where the adoption of online purchases is still relatively low, to leverage doctors as social influencers. The growth of online purchases will benefit patients, businesses, and the community. Online purchase is an easy way to buy products, interact with consumers, raise brand awareness, and reduce malnutrition, especially in remote areas where it is hard to get to traditional stores.

Asian businesses that wish to leverage doctors as social influencers to recommend online purchases must focus their actions on these three main points. Firstly, a marketing campaign that intends to leverage doctors as social influencers to digitize their patients must emphasize how easy it is to recommend online purchases and clarify the benefits of online purchases for patients. The benefits include saving time and making it easier to buy long-term daily medications, making patients more likely to take their medical nutrition, and reducing malnutrition. As the results clearly showed, Effort Expectancy (EE) and Performance Expectancy (PE) are the first and third drivers that affect a doctor’s intention. These factors will affect doctors’ intention to recommend their patients to purchase medical nutrition online. This study will give a clear direction of where the online purchase platform or e-pharmacy needs to focus and improve its feature or service to get more customers so that they can use this channel and make it more popular than the traditional medical store. To fully leverage the convenience of online shopping, it is essential to ensure that features are designed to be as easy to use as possible for customers.

Secondly, this study’s results showed that Social Influence (SI) is a significant factor in Asia since it is the second most important driver in this model. It would be best if communication channels used health associations, medical institutions, or doctors’ social media networks to share other people’s experiences to make doctors social influencers for online purchases. The reason is that Asians tend to talk to their families and friends, and businesses should pay close attention to what people say about their online purchases and how they feel about online reviews. Companies should also put in more time and money to promptly respond to customer complaints about online purchases. This action will also reduce the risks to public health that come with online pharmacies, like the sale of fake or low-quality products or drugs, as well as cybersecurity concerns, like consumer fraud and a lack of data privacy.

Thirdly, Facilitating Conditions (FC) and Anxiety do not influence doctors’ intention to recommend online shopping. Therefore, pharmaceutical companies do not have to worry about whether or not Sri Lanka’s market is ready for online purchase, and they could leverage doctors as social influencers. Currently, pharmaceutical companies are cautious about using online purchase channels because doctors might not support purchasing medical nutrition online since patients can buy medical nutrition online without a prescription. Additionally, businesses do not need to allocate resources or money to troubleshoot help, making it easier for people to buy things online.

Acknowledgment

This paper was presented at the 2022 MAG Scholar Conference in Business, Marketing, and Tourism (held in Bangkok, Thailand, 10th-22nd November 2022). We thank the conference participants and the managing editor for their comments on this paper.

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