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Factors That Influence the Intention to Use Self-Diagnosis Apps in Vietnam

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Abstract
Background: mHealth, which stands for Mobile Health, is a new concept that has emerged in recent years to talk about a new type of e-health. In mHealth medical activities are supported by mobile devices such as tablets and cell phones and these devices assist in tracking health status, support medical treatment, and support scientific research. The devices used in mHealth are not only limited to mobile phones but also includes laptops with wireless connection and hand-held wristbands that can collect and transmit information about the surrounding environment and the health status of the user. Using smartphones apps for medical and healthcare purposes is rapidly increasing. Some benefits of mHealth are connecting doctors and patients without meeting, tracking personal health data on smartphones, and performing treatments using the mHealth apps.
Methods: In this study, the factors that influence the intention to use self-diagnostic apps in Vietnam were examined. The research model was based on the Unified Theory of Acceptance and The Use of Technology model (UTAUT2) as well as the Theory of Perceived Risk (TPR). Data were collected through an online questionnaire and SPSS version 20 was employed to conduct regression analysis of the data of 482 respondents.
Results: The results revealed performance expectancy, effort expectancy, social influence, facilitating conditions, and social influence had a positive impact on the intention to use self-diagnostic apps. Furthermore, performance expectancy, effort expectancy, and hedonic motivation had a strong impact on users' intentions to use apps. While perceived risk had a negative effect, price value had no effect on users' intention to use the apps.
Conclusions: An examination of the factors that influence individuals' intention to use self-diagnostic apps in Vietnam can help app developers and marketers adjust their marketing strategies to meet customers' needs.
Keywords: Diagnosis; mHealth; apps; UTAUT2; Vietnam
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1. Introduction
1.1. Background
In recent years, an extremely large number of people have used smartphones. This phenomenon is particularly evident among young users. Mobile applications that assist individuals have also increased rapidly and significantly. Medical and health applications aimed at patients have become prominent. Mobile health applications (mHealth apps) are health-related applications that not only monitor and manage health and disease conditions but also contribute to enhancing patients' health. In 2014, more than 100,000 medical and health applications for smartphones were listed in the Apple App Store and Google Play Store (1). In 2017, health apps were downloaded 3.7 billion times on mobile devices (2). The most popular mHealth apps include health management, which involves exercise, lifestyle adjustments, diet, and nutrition, and chronic disease management, which comprises mental health, diabetes, and cardiovascular disease. Other categories of health apps include self-diagnosis, medication reminders, and electronic patient portal applications (3). Because of the convenience and plethora of information on the Internet, patients tend to conduct a self-diagnosis at home before going to a clinic or contacting a doctor when they experience any abnormal signs of health. A national survey of the Royal Pharmaceutical Society of England revealed that 51% of adults in the United Kingdom diagnosed themselves when feeling unwell or experiencing a medical symptom. A report on the frequency of Internet use to test and diagnose adult health problems in the United Kingdom in 2016 revealed that 41% of adults engaged in self-diagnosis via the Internet within a few months (4). Fox and Duggan showed that one-third of the adults surveyed from the United States noted that they employed online resources to self-diagnose or diagnose others (5).

Self-diagnostic apps at the Google Play Store and Apple App Store are easy to find. From the download metrics provided for Google Play applications, some self-diagnostic apps have been downloaded by approximately one million people. In particular, apps such as WebMD, Prognosis: Your Diagnosis and iTriage Health have been downloaded over a million times. According to the Nielsen Vietnam Smartphone Insights Report 2017, the number of smartphone users among mobile phone users increased from 78% in 2016 to 84% in 2017. Furthermore, 93% of all residents in secondary cities use mobile phones; of these, 71% use smartphones. While 89% of those who live in rural areas own a mobile phone, 68% of them possess a smartphone (6). In early 2018 in Vietnam, 70% of mobile subscribers were accessing the Internet via 3G or 4G. Statistics have also revealed Vietnamese people like to experience new apps; on average each individual downloads five new apps every month.

1.2. Objective

In developing countries and in particular, the rural areas thereof, lack of infrastructure, limited access to medicines and lack of medical staff are significant barriers to health care. Statistics have revealed that in the remote areas of Vietnam in 2014, there were only 7.9 doctors per 10,000 individuals. The features of mHealth applications and in particular, self-diagnostic apps can be beneficial for the early detection of diseases through symptoms. This leads to convenient and cost-effective ways to control particular diseases. The purpose of this study was to examine the factors that influence the intention to use and the potential for using self-diagnostic apps in Vietnam. This will assist app developers to know the feasibility of self-diagnostic apps expanding the market in Vietnam.

2. Theoretical basis

2.1. The trend of using self-diagnosis online

The number of individuals who use the Internet to find information about their health problems is increasing. A 2012 report revealed that the NHS Choices website, which provides a comprehensive portal for patients in England, was visited 15 million times each month (8). By 2014, this number had increased to 40 million. Of these, approximately five million views were taken care of by professionals who viewed the service as a reliable source of information and advice (9).

One-third of adults from the United States regard the Internet as a diagnostic tool (5). A 2013 report revealed that as a symptom testing tool, iTriage's free consumer health care app had been downloaded almost 10 million times and had 50 million users each year (10). Various self-diagnostic apps have been downloaded by a large number of users from the Google Play Store and Apple App Store. In particular, applications such as WebMD, Prognosis: Your Diagnosis and iTriage Health have been downloaded several million times.

In 1996, Vietnamese doctors and programmers jointly created a self-diagnosis and drug dictionary app called General Medical 1.0. In 1997, the authors developed Medical 2.0, which is software that works in Windows 16 or 32 bit. General users as well as doctors and pharmacists can search for commonly used drugs and essential information about common diseases and results of routine tests. The app also has a dictionary that includes symptoms and syndromes (11). Smartphone users in Vietnam have been able to search and install health apps via the Google Play Store or the Apple App Store easily. However, because the language used in most medical apps is English, users have difficulty accessing and using these applications. Although several apps with diagnostic functions use Vietnamese, these apps have a very limited number of users. In Vietnam, there are only a few medical apps, especially self-diagnostic apps, for phones. The majority of people who have signs of illness or poor health tend to go to pharmacies, explain their symptoms to the pharmacy assistants, and obtain the necessary drugs. If their symptoms are severe and urgent, they usually go to a clinic or hospital. If their symptoms are mild and negligible, a portion of young people use a search engine such as Google to find information related to the symptoms. Knowledge about the factors that influence users' intentions will assist with the development of self-diagnostic apps that are suitable for the mHealth market in Vietnam, which will help many people when their symptoms appear.

Benefits of self-diagnostic applications

Quickly reduce the anxiety

Individuals often become worried when they exhibit any signs of illness or abnormal health. A diagnosis, regardless of whether it is self-found or determined by a medical professional, may bring relief to the individual (1). When individuals make a self-diagnosis through a mobile app, they quickly find the symptoms from which they are suffering. They generally feel reassured if their symptoms are common. They usually calm down on realizing that their symptoms are fairly common and will soon pass, without the need to consult a doctor (12).

Time Saver

Pursuing self-help efforts may save people time they would have spent with a therapist or doctor who could help them with their problems (13). Self-diagnosis by looking for symptoms on a mobile app can be completed quickly while making an appointment with a doctor may be time-consuming. Furthermore, waiting for an appointment can cause much stress and worry about an illness that may not be serious. Symptoms generally disappear by themselves before the appointment. Thus, looking up symptoms may calm the individual (12). On the other hand, waiting for physicians when an individual is suffering from the symptoms of a serious disease can delay the diagnosis and timely treatment.

Better preparation for an appointment with physicians

Self-diagnosis helps patients obtain more information about their current condition. If an individual has an idea of what their condition is before seeing a doctor or physician, they may feel calmer (1). This may also assist individuals to discuss their symptoms with the doctor as they may have a clear idea of their condition and what they need to do (12). Furthermore, they will have a better understanding of the doctor's view of their condition when it is discussed with them.

Mobility, inexpensive, easy to access and use

Most people have smartphones, which they always carry around. Consequently, accessing apps to perform self-diagnosis is extremely convenient and fast, and can be done when and wherever convenient. Due to their simple format and location on mobile wireless devices, apps can be easily downloaded. Furthermore, they can be carried around for reference, updating information, and commenting, which can be shared with others (1). Self-diagnostic apps on mobile phones are usually free or cheap. These apps are thus inexpensive methods to benefit those who are struggling financially. Self-help may be one of the only favorable options available to those who live in rural areas or small towns (13). A rapid diagnosis would benefit the poor and vulnerable significantly. Therefore, mobile self-diagnostic apps make it easy for patients to access medical information, which may not be available in the area where they live.

Privacy

Self-diagnostic apps can help individuals who are private and feel uncomfortable sharing their medical problems with others. Furthermore, their self-diagnosis may save them the embarrassment of an awkward encounter with the doctor. However, although looking up symptoms may assist a patients' peace of mind, it is recommended that they still consult a doctor. Physicians and doctors are trained professionals who should help their patients and not judge them. Alternatively, patients could consult an online doctor for more information (12).

2.2. Introduction to the theory of technology application

Theory of Reasoned Action (TRA): The TRA model posits that behavioral intention is the most important factor predicting consumer behavior in which two factors of user attitude and subjective standards affect use behavior (14). In the TRA model, the user's attitude is measured by positive and/or negative perceptions about the properties of the product. Standard subjective factors show the influence of social relations on individual users.

Theory of Perceived Risk (TPR): Bauer (1960) argued that the perceived risk behavior of technology products includes perceived risks related to products and services as well as perceived risks related to online payment (15). The former involves customers' concerns about loss of features, financial loss, and the amount of time lost when using technology products and/or services. The latter includes risks such as confidentiality, safety, and total loss that may occur when consumers conduct transactions electronically.

Theory of Planned Behavior (TPB): A perceived behavioral control factor was added to the TRA model to form the TRB. Behavioral control components reflect whether it is easy or difficult to conduct behavior. This is dependent on the availability of resources and opportunities for behavior. TPB assumes that behavior can be predicted or explained by behavioral trends to implement that behavior. Behavioral trends are assumed to include motivational factors that affect behavior and are defined as the level of effort individuals expend when trying to perform that behavior (16).

Technology Acceptance Model (TAM): The TAM, which was developed by Fred Davis and Richard Bagozzi, explains the factors that are related to the adoption of technology and the intention to use technology (17). Perceived usefulness and perceived ease to use are two factors that directly affect the user's attitude. The TAM examines the relationship and impact between the following factors: perceived usefulness, perceived ease of use, attitude of use, intention to use, and usage behavior in accepting users' technology.

Unified Theory of Acceptance and Use of Technology model (UTAUT model): Venkatesh and David (2003) incorporated all the theories mentioned in the UTAUT model. The TRA, TPB, and TAM have the most influence on UTAUT. Furthermore, UTAUT has four core elements that have an impact on behavioral intention and use behavior such as performance expectancy, effort expectancy, social influence, and facilitating conditions (18). Subsequently, Venkatesh et al. (2012) added factors such as hedonic motivation, price value, and habits into the original UTAUT model to form UTAUT2 (19).

3. Methods

Research model

The UTAUT2 model was employed in this study. The main variables of the model include performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), and perceived risk (PR). The six variables have a direct impact on the user's intention to use self-diagnostic apps A further variable includes demographic factors such as age, gender, education level, and occupation. The main variables of the model are depicted in Figure 1.

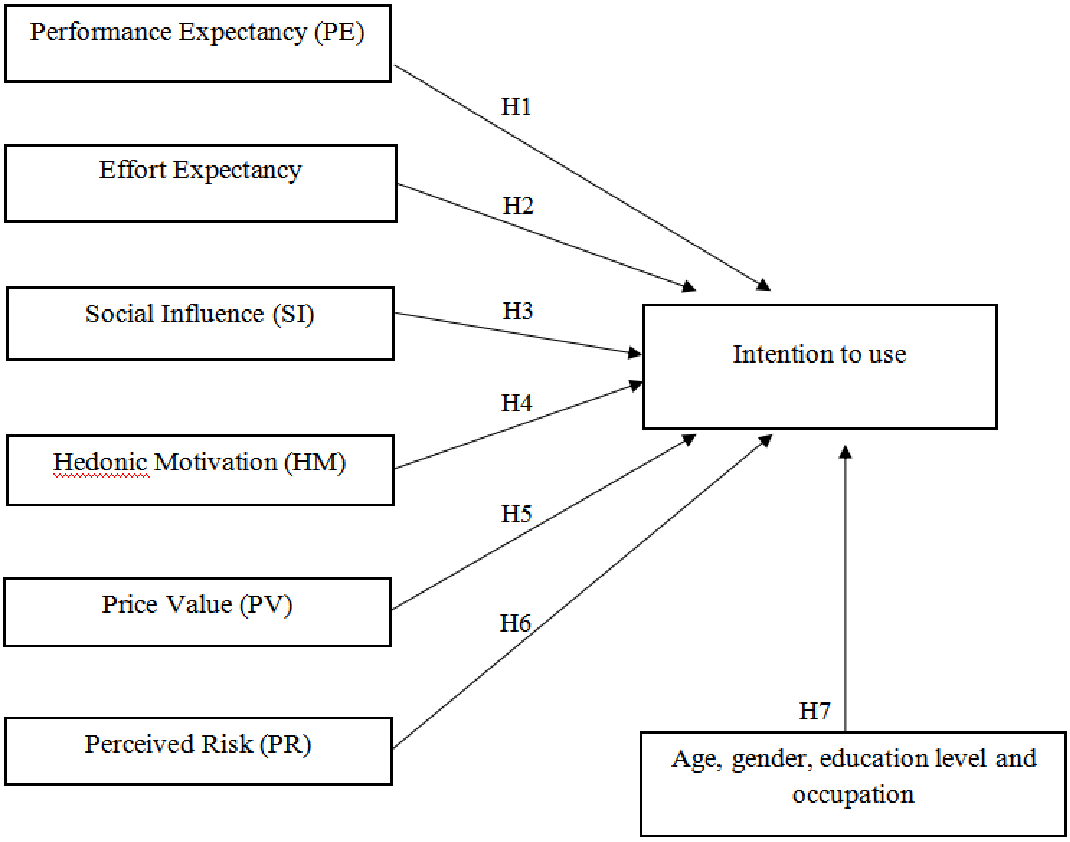

Figure 1: Main variables of the UTUAT2 model

PE is the extent individuals believe that using a self-diagnostic app will help them acquire certain benefits. Individuals tend to adopt technology so that they can help themselves more. Useful scales for using a self-diagnostic app may include: speed and convenience, saving money and time, preparing before seeing a doctor, and reminding patients to pay more attention to health care. Accordingly, the first hypothesis was formulated:

H1: Performance expectancy impacts positively on the user's intention to use self-diagnostic apps.

EE is primarily based on ease of use, complexity, and level of difficulty. The ease of use of the system is the degree to which an individual believes that using a self-diagnostic app on a smartphone will not require much physical and mental effort. In the context of using smartphone apps, an easy-to-use system needs user-friendly interfaces such as clear and visible steps, relevant and understandable content, easy-to-use functions, and information related to health symptoms should be easy to search for. Therefore, the second hypothesis was as follows:

H2: Effort Expectancy impacts positively on the user's intention to use self-diagnostic apps.

SI is the extent to which an individual is aware that significant others recommend they use the self-diagnostic app. The behavior of family members, friends, colleagues, and people around them also tends to affect the use behavior of that individual. Accordingly, the third hypothesis was formulated: H3: Social Influence impacts the user's intention to use self-diagnostic apps positively.

HM is defined as the fun or pleasure derived from using technology. Individual's living standards are constantly improving. The pursuit of technical utility is not only to achieve certain functions but to enjoy doing so. Venkatesh et al. (2012) added hedonic motivation as a predictor of consumer intent to use technology.

The fourth hypothesis was as follows H4: Hedonic Motivation impacts the user's intention to use self-diagnostic apps positively.

PV is the cost that may influence a user's intention to use the technology. Prices are often associated with the quality of a product and/or service to determine the perceived value of that product or service. Jing Li revealed that some participants said that free values affect their consumption behavior (20). When using an online service, many individuals are concerned about the cost thereof. Ma et al demonstrated that the cost-saving aspect of using self-service technology (SST) has a positive effect on customer satisfaction (21). Altmann, and Gries found that cost factors involved in using mHealth apps were negligible (22). Consequently, PV was included in the analysis to determine if the price has an impact on individuals' intention to use self-diagnostic apps. The fifth hypothesis was as follows:

H5: Price value has a positive impact on the user's intention to use self-diagnostic apps.

Bauer (1960) stated that PR is related to uncertainty and the consequences of consumers' actions. According to the TPB, perceived risk can reduce uncertain consumer behavior control and will have a negative impact on their

behavioral decisions. Perceived risk has a certain impact on the user's decision to use self-diagnosis apps. Accordingly, the sixth hypothesis was formulated:
H6: Perceived risk has a negative impact on the user's intention to use self-diagnostic apps.
Demographic factors may have various impacts on the intention to use self-diagnosis apps. The seventh hypothesis was:
H7: Age, gender, education level, and occupation have different impacts on the intention to use self-diagnostic apps.

Research design

This study was conducted through two steps: a qualitative preliminary study and a formal quantitative study: In the qualitative preliminary study, in-depth interviews were conducted with 10 people who used self-diagnostic apps to determine the scale, which was the basis for developing the questionnaire in the formal quantitative study. In the latter step, data were collected through an online questionnaire found on the following website: www.wenjuan.com. Convenience sampling was employed. A total of 516 questionnaires were completed; of these 34 were deemed invalid and thus, the data collected from 482 questionnaires were analyzed.

Intention to use self-diagnostic apps was based on the six main components of the UTUAT2. This included 26 scales. Furthermore, three scales were added. Thus, there were 29 observed variables. A five-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree), was employed to assess the statements in the questionnaire. The software used in this study was SPPS version 20. The data were collected and analyzed by employing the following tools: Cronbach's alpha to determine the reliability of the scale; exploratory factor analysis (EFA); and correlation and regression analyses of key components and their relationships in the model and the intention to use self-diagnosis applications among groups including gender, age, education, and occupation.

4. Results

Sample survey information

The questionnaire assessed the respondents' gender, age, educational level, and occupation. The results revealed the sample comprised 304 women (63.1%) and 178 men (36.9%). Of the respondents, 246 (51%) were between the ages of 18 and 24 years, 207 (42.9%) between the ages of 25 and 30, 28 (5.8%) between 31 and 41 years, and one (0.2%) between 41 and 50 years of age. Most of the respondents (352; 73%) were university graduates. The respondents were engaged in the following occupations: 164 (34%) were students, 113 (23.4%) were office workers, and 40 (8.3%) were specialists. Thus, the majority of the respondents were young and educated. The demographic information of the respondents is presented in Table 1.

Table 1: Demographic information

		Quantity	Ratio (%)
Sex	Male	178	36.9%
	Female	304	63.1%
Age	18–24	246	51.0%
	25–30	207	42.9%
	31–40	28	5.8%
	41–50	1	0.2%
Education	Primary school	1	0.2%
	Junior high school	17	3.5%
	High school	69	14.3%
	Intermediate/Vocational school	18	3.7%
	College/ University	352	73.0%
	master's degree and higher	25	5.2%
Job	Student/PhD student	164	34.0%
	Government officials	9	1.9%
	Business management (including junior and middle and senior management)	16	3.3%
	Office staff	113	23.4%
	Specialists (doctors/lawyers/sports/reporters/teachers, etc.)	40	8.3%
	Unskilled labor	20	4.1%
	Service staff (salespeople/shop staff/waiters, etc.)	25	5.2%
	Self-employed/contractor	21	4.4%
	Freelancer	19	3.9%
	Agriculture, forestry, livestock, and fishermen	4	0.8%
	Temporarily not working	33	6.8%
	Other jobs	18	3.7%

Analyze the reliability of the scale

The collected data was analyzed by employing SPSS (Statistical Package for the Social Sciences) version 20. The results of Cronbach's Alpha (Table 2) revealed that all scales had high reliability (> 0.7) and were thus included in the EFA.

Table 2: Cronbach's alpha

The variables	Cronbach's alpha
Performance Expectancy	0.897
Effort Expectancy	0.863
Social Influence	0.849
Hedonic Motivation	0.891
Price Value	0.897
Perceived Risk	0.788
Intention to use	0.829

The results of the EFA revealed a factor loading of observed variables greater than 0.7, Bartlett testing with Sig. = 0.000, coefficient KMO = 0.843 (> 0,5), total variance extracted by 71.079 (> 50%), in addition, sig value. <0.05. Thus, six factors with Eigenvalues greater than 1 were extracted from the 26 observed variables. Therefore, the scales were acceptable. The results of the EFA are shown in Tables 3 and 4.

Table 3: Results of the KMO analysis

Kaiser–Meyer–Olkin measure of sampling adequacy.		0.835
Bartlett's test of sphericity	Approx. Chi-Square	7231.130
	Df	325
	Sig.	0.000

Table 4: Results of the EFA analysis

Variable	Component					
	1	2	3	4	5	6
PV5	0.895					
PV1	0.840					
PV4	0.829					
PV2	0.820					
PV3	0.805					
PE5		0.862				
PE2		0.813				
PE1		0.811				
PE3		0.803				
PE4		0.776				
HM1			0.917			
HM3			0.825			
HM2			0.798			
HM4			0.777			
EE2				0.858		
EE1				0.816		
EE3				0.808		
EE4				0.770		
SI1					0.858	
SI2					0.834	
SI3					0.788	
SI4					0.744	
PR3						0.848
PR2						0.803
PR1						0.705
PR4						0.700
Eigenvalues	6.255	3.772	2.441	2.404	1.960	1.649
% of Variance	24.059	14.507	9.388	9.246	7.537	6.341
Caculative %	24.059	38.566	47.954	57.201	64.738	71.079

Before the regression analysis, it was necessary to analyze the linear correlation relationship between the dependent variable and each independent variable as well as the relationship between each independent variable. Pearson Correlation Coefficient was employed to determine these relationships. The absolute value of r indicates the severity of the linear relationship (r has a value between -1 and 1). The results are presented in Table 5.

Table 5: Matrix coefficient correlation

Correlations							
	PE	EE	SI	HM	Cost	PR	INT
PE	1						
EE	0.290**	1					
SI	0.203**	0.303**	1				
HM	0.375**	0.344**	0.299**	1			
PV	−0.105*	0.015	0.063	−0.049	1		
PR	−0.287**	-0.108*	−0.245**	−0.158**	0.119**	1	
INT	0.551**	0.512**	0.465**	0.574**	−0.093*	-0.450**	1

**Correlation is significant at the 0.01 level (2–tailed).

*Correlation is significant at the 0.05 level (2–tailed).

The matrix coefficient correlation (Table 5) revealed that the dependent variable *intention to use* had a close linear correlation with the following five independent variables: PE, EE, SI, HM, and PR at the expected level. Correlation was considered significant at the 0.05 level, and the correlation coefficients between the oscillating variables in the paragraph [0.450; 0.574], satisfy the condition $r \in [-1; 1]$. All the variables were satisfactory and thus, included in the multivariate linear regression analysis. However, the independent variable PV with the correlation coefficient r = [0.093] had no effect on users' intention to use self-diagnostic apps. If all VIF indicators are less than 10, multicollinearity does not occur. The VIF values are presented in Table 6, which shows the model regression weights.

Table 6: Results of multivariate regression analysis

Model	Unstandardized coefficients	Standardized coefficients	T	Sig.	Collinearity statistics
	B	Beta			VIF
(Constant)	1.147		5.791	0.000	
PE	0.201	0.252	8.091	0.000	1.288
EE	0.188	0.254	8.357	0.000	1.230
SI	0.212	0.190	6.269	0.000	1.218
HM	0.317	0.294	9.428	0.000	1.300
PV	−0.038	−0.038	−1.360	0.175	1.034
PR	−0.253	−0.253	−8.626	0.000	1.150

The results depicted in Table 6 revealed that all the VIF indicators were less than 10 thus indicating that the independent variables were not closely related. Thus, the regression model did not display multicollinearity. However, the results revealed Sig. = 0.175 (> 0.05) and thus, the PV variable was not statistically significant. When this element was excluded from the model and regression analysis conducted, corrected regression analysis results were obtained, which are displayed in Table 7

Table 7: Results of calibrated multivariate regression analysis

Model	Unstandardized coefficients	Standardized coefficients	t	Sig.	Collinearity statistics
	B	Beta			VIF
(Constant)	1.074		5.628	0.000	
PE	0.204	0.255	8.215	0.000	1.280
EE	0.187	0.253	8.312	0.000	1.229
SI	0.207	0.185	6.155	0.000	1.205
HM	0.319	0.296	9.479	0.000	1.298
PR	−0.257	−0.258	−8.826	0.000	1.136
R square	0.642				
Adjusted R square	0.638				
F value	170.805			0.000	

Linear regression equation:

$Y_{Intention} = \beta PE + \beta EE + \beta SI + \beta HM + \beta PR$

Correction coefficient $R^2 = 0.638$, which means that five independent variables explained 63.8% of the variance of the dependent variable. Value F's Sig. = 0,000 (<0.05) and thus, hypothesis H0 $R^2 = 0$ (or $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$) is rejected so the linear regression model is suitable for the data set and can be used. Therefore, hypotheses H1, H2, H3, H4, and H6 were accepted. The regression equation with variables with a standardized coefficient on intention to use self-diagnostic apps is as follows:

$Y_{Intention} = 0.255\ PE + 0.253\ EE + 0.185\ SI + 0.296\ HM - 0.258\ PR$

The results revealed that the intended use variable was affected by the independent variables. The variables, PE, EE, SI, and HM had a positive impact on the intention to use while PR had a negative impact on the intention to use.

Testing differences according to qualitative variables

To test the difference in intention to use between the male and female users, we conducted an independent sample t-test. Table 8 reveals that the Levene Test was valid for Sig. = 0.677> 0.05. Thus, the variance of the two groups was not different. Consequently, in the results of the independent sample t-test, we used the results of the equal variance with Sig. = 0.703> 0.05. Therefore, there was no difference between the men and women in relation to the intention to use self-diagnostic apps.

Table 8: Results of t- test by gender

		Levene's test for equality of variances		t-test for equality of means	
		F	Sig.	t	Sig. (2–tailed)
Intention	Equal variances assumed	0.173	0.677	−0.382	0.703
	Equal variances not assumed			−0.379	0.705

We conducted a one-way ANOVA test to verify the difference in intention to use between the different age groups, education levels, and occupations. The results presented in Table 9 show the Levene test has Sig. values greater than 0.05 (significance level) and the F test has Sig. > 0.05. Consequently, there was no difference in intention to use the self-diagnosis apps in relation to age and education level.

Table 9: Results of One-way ANOVA

Variable	Levene statistic	Sig.	F	Sig.
Age	0.345	0.708	0.226	0.878
Education level	1.417	0.227	0.465	0.802

The results in relation to occupation revealed that the Levene test has Sig. = 0.011 (<0.05). The assumption of uniform variance between groups of qualitative variable values was violated. Therefore, the variance between the working groups was not equal. Therefore, we were unable to use the ANOVA table but had to employ the Welch test for assuming a uniform variance.

Table 10: Results of Welch test

	Levene statistic	Sig.
	2.258	0.011
Welch		0.878

The results of the Welch test result revealed Sig. = 0.878 (> 0.05). Therefore, there was no statistically significant difference in the intention to use self-diagnostic apps of users in different occupations.

5. Discussion and conclusion

The model of factors influencing the intention to use self-diagnostic apps outlines six factors that may have an influence thereof. The results revealed five factors, namely, HM, PE, EE, SI, and PR affected user intention. The factors HM, PE, EE, and SI had a positive a positive impact on the intention to use self-diagnostic apps. Of these, HM had the strongest impact on users' intentions to use.

The factor PR had a negative impact on intention to use self-diagnosis apps. At present, the security of information on the Internet in Vietnam is questionable. Consequently, many individuals worry that their personal information and payment information will not be secure. The problem of online payments on websites or mobile apps in Vietnam is prevalent. Individuals worry that the personal information and banking details are not safe. To compete in the market as well as to ensure that self-diagnosis apps are not risky, it is imperative for suppliers to have a consumer protection policy to ensure the safety of users' information. It is also recommended that a guide be written to help users secure their personal information. The factor, PV did not really impact on intention to use. This suggests that consumers are willing to pay for a self-diagnostic app if it meets their needs and they are satisfied with the app's quality. Demographic factors such as gender, age, education, and occupation did not have an influence on the intention to use self-diagnostic apps. Of the respondents, 20.5% said that they regularly go for a health examination every six months and 51.7% said that they would go to hospital if they experienced unusual health symptoms. Only 5% of respondents knew about and had used self-diagnostic apps. It is possible that there are a limited number of mobile health apps and the quality of these is below standard. For mHealth apps and in particular, self-diagnostic apps to become more popular, it is imperative for developers to improve their quality as well as marketing strategies so that information is more widely disseminated.

6. Limitations and further research

The respondents were mostly young people (18-30 years old) and lived in large cities such as Ho Chi Minh City and Hanoi. This is a limitation in that only a certain target group was represented. It is recommended that future studies include a more representative Vietnamese population.

Furthermore, as noted previously, only 5.04% of the respondents had used self-diagnostic apps. This suggests that the respondents' knowledge about self-diagnostic apps was lacking. Consequently, this study may only be meaningful in relation to the model. However, this study has implications for other research in the field of mobile health. At the same time, app developers and marketers should take cognizance of the factors that influence the intention to use self-diagnostic apps and create apps that are accessible to users. As noted, most of the respondents were young people who were often exposed to technology. It is recommended that more in-depth studies be conducted on factors that influence the intention to use self-diagnostic apps in middle-aged and older adults. The majority of respondents were students and office workers who lived in urban areas. It is recommended studies be conducted in rural areas where medical facilities and medication are limited.

Furthermore, as noted, the respondents lacked knowledge and experience in using self-diagnostic apps. It is recommended a follow-up study be conducted to analyze whether knowledge actually affects the intention to use self-diagnostic apps on smartphones. It is believed that if more people who use self-diagnostic apps are included in a study, the results will be more reliable.

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