Moderating roles of user's intention to use LINE official account in healthcare context: body mass index

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ABSTRACT

This study aimed to investigate the extended factors based on the technology acceptance model, and the moderating roles of customer behavioral intention factors to use information technology. This research is a questionnaire-based survey with convenience sampling approach where 386 cases were collected from healthcare customers. For statistical analysis, the study used SmartPLS as a tool for regression analysis and descriptive statistics. The findings revealed the influence of social norm on customer behavioral intention to use information technology in the healthcare context as significant factors at 0.001. In addition, the results indicated the small effect of two moderating variables in the proposed model. First, the problematic body mass index (BMI) can be a moderator on the relationship between social norm and customer behavioral intention to use technology at a significant level of 0.05. Second, the technology experience can moderate the relationship between perceived ease of use and customer behavioral intention to use technology at a significant level of 0.05. The proposed model may guide for future exploration, especially information services in healthcare businesses and developers.

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1. INTRODUCTION

Nowadays, most businesses usually provide their information technology for customer services. For example, company website, mobile application, Facebook, LINE official account (LINE OA), and chatbot. In Thailand, more than 54 million users are registered to LINE and the growth rate was 56% in the past decade [1]. LINE Thailand recorded the most popular group categories for chatting; friends (82%), family (80%), work (77%), and school (27%) [1]. In addition, 77% of users reported that family chat groups help them to improve ties among family members. A Thai LINE user holds an average of seven groups for friends, four groups for family, five groups for school, and nine groups for work [1]. Therefore, heavy use of group chats in LINE platform can influence the user work-life balance. Hatyai Chivasuk is a healthcare center related to traditional Thai medicine, massage, and spa which focuses on the body mass index (BMI) of customers. As a result, Hatyai Chivasuk provides healthcare information and services via the LINE platform for customers, namely Hatyai Chivasuk healthcare system (HC-HS). However, as the HC-HS is a newly developed technology among customers, the operators lack understanding the customer acceptance, especially for the problematic BMI as the moderating variable.

For the technology adoption of Hatyai Chivasuk, it is necessary to understand the factors of customer acceptance to technology use. The technology acceptance model (TAM) is a well-known model to understand the intention of a person to use technology [2]–[7]. However, research gaps remain in the disagreed results of factor influences in previous studies and TAM such as the relationship between perceived usefulness and behavioral intention to use technology [8], perceived ease of use and user's behavioral intention [8], and the perceived ease of use and user's intention to use technology [9]. In addition, the previous works indicated important influences on user's intention to use technology in the healthcare context [8], [9]. Other empirical studies extended BMI [10], [11] and technology experience [12] as moderating variables. Therefore, extended studies based on TAM in the healthcare context are required to include more variables to better predict behavioral intentions of the customer. To prove the abovementioned gaps, this research aimed to investigate the proposed model and test hypotheses in the healthcare context, especially in the focus of information technology. In this work, we propose a model based on TAM with the extended factor of social norm, and two possible moderators, such as problematic BMI and technology experience.

2. LITERATURE REVIEW AND RELATED WORK

This section provides an overview of the literature related to the adopted technology and proposed model in four parts. The four parts are: i) Hatyai Chivasuk healthcare system (HC-HS), ii) technology acceptance model, iii) social norm on behavioral intention to use HC-HS, and iv) technology experience and problematic BMI as moderating variables. Further details are explained below.

2.1. Hatyai Chivasuk healthcare system (HC-HS)

The HC-HS was developed in the LINE OA platform by Hatyai Chivasuk. It provides services and information related to BMI. For example, knowledge of problems related to BMI, BMI calculation, navigation of exercise places, food and drinks based on life elements, events, promoting activities, promotions of Thai massage and spa, news, HC group chat, individual consultancy, and self-healthcare knowledge. This information technology was designed based on a user-friendly interface (UI) and user experience (UX). The general menu was outlined with a rich menu at the bottom of the screen. Most information is provided in graphic-content rich messages and card-based messages as presented in Figure 1. In addition, customers can chat in text and receive real-time artificial intelligence (AI) response messages. The LINE OA can be used to guide patient care and encourage patients to take better care of themselves [13]. Furthermore, the success of telemedicine follow-up services via LINE OA among Thai people [14]. Therefore, this study expected customer acceptance in HC-HS in healthcare context.

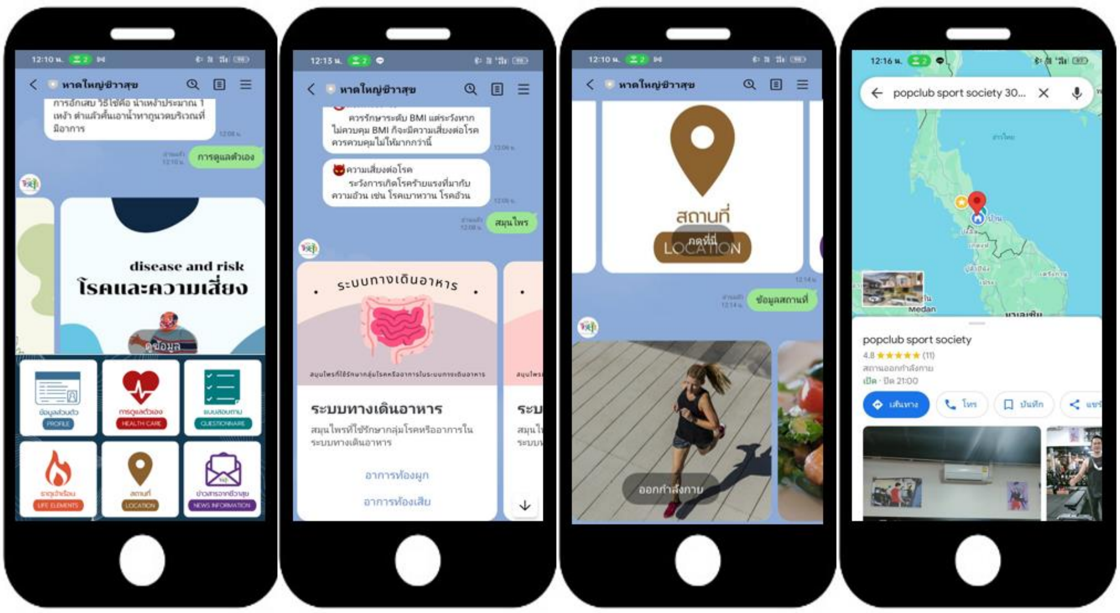

Figure 1. Screen examples of HC-HS

2.2. Technology acceptance model

Technology acceptance model (TAM) [1] is a model to enhance understanding why users accept or reject a new information technology, and how to improve user acceptance to the proposed technology. Users' behavioral intention to use technology (BI) depends on their attitudes toward technology. The perceived usefulness (PU) and perceived ease of use (PEU) were the key factors of users' attitudes toward technology [2]. PU refers to the degree to which a person believes that using a particular system would enhance his or her job performance. PEU refers to the degree to which a person believes that using a particular system would be free from effort. All relationships between the variables in TAM are presented as Figure 2.

However, many previous studies omit the user attitudes toward technology in their works as psychological variables was difficult to measure [3]–[7]. Furthermore, some researchers found non-significant relationships in TAM-based models with extended variables. For example, studies [8], [15] did not find any influence of PU on BI in the healthcare context, study [9] illustrated the insignificant influence of PEU on PU in healthcare technology and demonstrated no significant relationship between PEU and BI in IoT. Based on the above discussion, the following hypotheses were generated to investigate three relationships in HC-HS context:

$H1$: $Perceived\ usefulness\ influences\ customer\ behavioral\ intention\ to\ use\ HC-HS.$
$H2$: $Perceived\ ease\ of\ use\ influences\ customer\ behavioral\ intention\ to\ use\ HC-HS.$
$H3$: $Perceived\ ease\ of\ use\ influences\ perceived\ usefulness.$

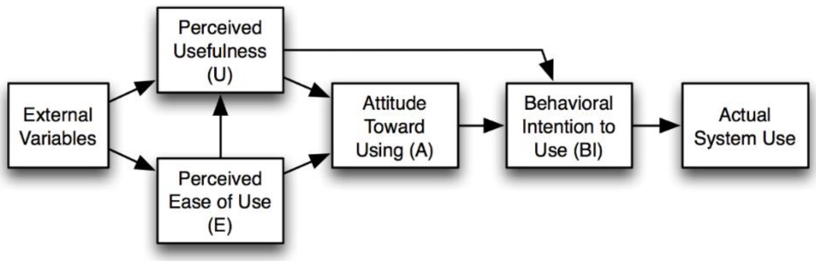

Figure 2. Technology acceptance model [1]

2.3. Social norm on behavioral intention to use HC-HS

Social norm (SN) refers to people's societal pressure when they decide on their actions [16]. In various studies, other terminology applies to the social norm such as norm, subjective norm [8], [9] and social influence [15], [17]. Several researchers found social influence on behavioral intention to use technology to be positive [8], [15], although some previous study [15] demonstrated no significant relationship between SN and BI. In this study, the social norm may be a factor of user intention to use HC-HS in healthcare context. The fourth hypothesis emerges as follows:

$H4$: $Social\ norm\ influences\ behavioral\ intention\ to\ use\ HC-HS\ in\ healthcare\ context.$

2.4. Technology experience and problematic BMI as moderator variables

In this study, the technology experience referred to a person who has or does not have technology experience in LINE OA. According to the unified theory of acceptance and use of technology (UTAUT), UTAUT [12] indicated that user experience can strengthen the relationship between factors (effort expectancy and social influence) and behavioral intention. Furthermore, user perceptions of new technology will change when they acquire information technology skills and gather experiences [18]. In addition, some previous study [19] indicated in their work that people with different levels of technology experience will have different learning skills. Therefore, technology experience may be the moderator of the associations of PEU and BI, and SN and BI. The hypotheses should be formulated as follows:

$H5$: $Technology\ experience\ strengthens\ the\ relationship\ between\ PEU\ and\ BI.$
$H6$: $Technology\ experience\ strengthens\ the\ relationship\ between\ SN\ and\ BI.$

Body mass index (BMI) is a measure of body fat based on weight (kilogram) and height (meter). A high BMI can indicate high body fatness or overweight, while a low BMI means low body fatness or underweight. The formula is shown in (1).

$$BMI = weight/height^2 \quad (1)$$

There are four levels of BMI to indicate the health risk in Asian older than 20 years [20] as shown in Table 1. BMI is a parameter for diabetes mellitus prediction [21] and cause of cardiovascular disease (CVD) [22], [23]. In addition, BMI is a key of physical activity [24] and the knowledge of BMI on mobile application will help adult with obesity to have a better and healthy lifestyle [25].

Table 1. The Asian's BMI and levels of health risk

Level	BMI (kg/m^2)	Classification	Physical
1	< 18.5	Underweight	Minimal
2	18.5-22.9	Normal weight	Minimal
3	23.0-24.9	Pre-obesity	Increased
4	25.0-29.9	Obesity	High
5	>= 30	Severely Obesity	Very high

In our proposed model, problematic BMI refers to a person's problem in terms of being overweight or underweight. The findings in [26] indicated the different BMI groups in terms of frequent upload photo of meal photos and changes in body weight. In addition, most empirical studies suggested the BMI as a moderating variable in healthcare context [10], [11] whereas some previous study [27] found BMI as insignificant moderator in their research. To confirm the above discussions, this study assumed Problematic BMI as the moderating variable on the related associations of PU and BI, and SN and BI. The hypotheses were presented as follows:

$H7$: $Problematic\ BMI\ strengthens\ the\ relationship\ between\ PU\ and\ BI.$
$H8$: $Problematic\ BMI\ strengthens\ the\ relationship\ between\ SN\ and\ BI.$

From all hypotheses stated above, our proposed research model based is presented in Figure 3. This study aimed to investigate three factors of behavioral intention to use HC-HS such as perceived usefulness, perceived ease of use, and social norm. The technology experience and Problematic BMI were considered as moderating variables and the behavioral intention was a dependent variable.

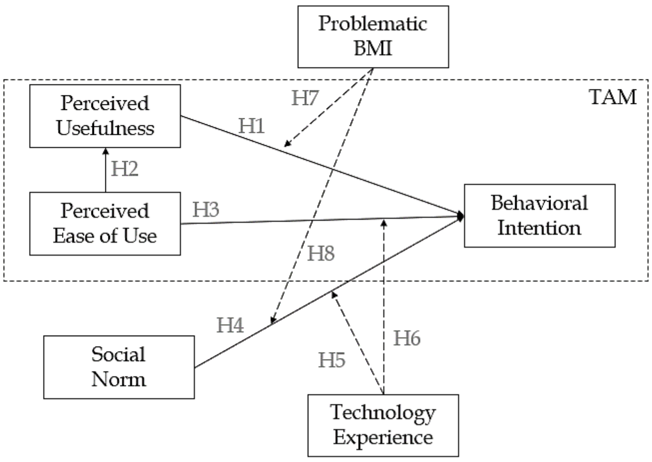

Figure 3. Research model based on TAM

3. METHOD

For this study, data were collected from customers of Hatyai Chevasuk in Thailand using a self-administered questionnaire. The sample size was 384 which is sufficient for regression analysis [28]. To support the incomplete questionnaire, this study distributed 400 questionnaires to customers using convenient sampling. Finally, 386 complete questionnaires were returned for analysis. The questionnaire was divided into three sections: i) demographic information, ii) information about four variables (perceived usefulness, perceived ease of use, social norm, and behavioral intention to use technology), and iii) additional suggestion. Participants were asked to indicate their agreement or disagreement with several statements on a five-point Likert scale (1=strongly disagree, 2=disagree, 3=not sure, 4=agree, and 5=strongly agree). In section 2 of the administered questionnaire, we adopted measures from reliable measurements in previous researches [3], [9], [12], [21] as shown in Table 2. All adopted items had values of Cronbach's Alpha or composite reliability (CR) higher than 0.70. There were six measures which consisted of three factors (perceived usefulness, perceived ease of use, and social norm), two moderating variables (technology experience and problematic BMI), and one dependent variable (behavioral intention). Analysis was performed with SPSS and SmartPLS. The SPSS was used for descriptive analysis, meanwhile the SmartPLS was used for reliability analysis, validity analysis, and regression analysis.

Table 2. Research measurement

Item	Measurement	Source
Perceived usefulness		
PU1	The news of HC-HS is very useful.	[3], [12], [21]
PU2	HC-HS is very convenient to access my healthcare history.	
PU3	HC-HS supports my needs well in terms of exercise places.	
PU4	I can use HC-HS to recommend healthy restaurants.	
Perceived ease of use		
PEU1	Usage learning does not take a lot of time.	[3], [12], [21]
PEU2	Using HC-HS is easy.	
PEU3	Menu categories are easy to access	
PEU4	Using chat for health consulting is easy	
Social norm		
SN1	Others' opinion about HC-HS affects my intention to use it	[9], [12]
SN2	People who are important to me think that I should use HC-HS for healthcare services.	
SN3	I will use HC-HS if I see people around me use it.	
Behavioral intention		
BI1	I intend to use HC-HS in the future.	[12], [21]
BI2	If I need self-healthcare information, then I will consider to use HC-HS,	
BI3	I will recommend others to use HC-HS.	
BI4	In the future, I will reserve the activities via HC-HS.	
Technology experience (have/not have)		
Problematic BMI (have/not have)		

4. RESULTS AND DISCUSSION

This section presents the analyzed procedures and experiment results in three steps: i) descriptive analysis, ii) measurement analysis, and iii) structured equation modelling (SEM) analysis and hypothesis testing. The descriptive analysis specified the profiles of research volunteers such as gender, age, education, income, and experience on LINE application. With the aid of the measurement analysis evaluated three aspects such as convergent validity, reliability, and discriminant validity. Finally, SEM analysis provided the results of hypothesis testing.

4.1. Descriptive analysis

For demographic analysis, 386 complete questionnaires were analyzed using descriptive statistics as presented in Table 3. In this study, the proportions of males and females were 47.4% and 52.6%, respectively. From the perspective of age, the number of people aged between 51 and 60 was the largest population, with 107 people, accounting for 27.7% of the sample. In terms of education level, there were 203 people with bachelor's degree, accounting for 52.6% of the population; 94.8% of the respondents had income less than 30,001 THB. The number of people who never had any experience in LINE application was higher (52.1%) than others (47.9%).

4.2. Measurement analysis

There were two stages to evaluate the measurement: i) convergent validity and reliability and ii) discriminant validity. Convergent validity analyzed the factor loading between measures in the same constructs. Reliability analysis of scale showed consistent results with repeated measurements. Discriminant validity analyzed the correlation between measures in different constructs.

4.2.1. Convergent validity and reliability

The results showed that Cronbach's Alpha and composite reliability (CR) were higher than 0.70, indicating the reliability of measurement in this study was accepted [28]. In addition, the average variance explained (AVE) in each latent was greater than 0.50, and the factor loadings were higher than 0.70 as presented in Table 4. These results indicated good convergent validity [28].

4.2.2. Discriminant validity

Three evaluations were applied to analyze discriminant validity: Fornell-Larcker criterion, cross-loading, and Heterotrait-Monotrait ratio (HTMT). From the Fornell-Larcker Criterion, results showed that all square roots of AVEs (diagonal values) were higher than their latent as presented in Table 5, thus supporting Fornell-Larcker criterion [29]. The HTMT values are also less than 0.90, indicating no discriminant validity [30], [31]. In addition, all cross-loading values were higher than 0.70 [32]–[35], hence three evaluated results illustrated the good determinant validity.

Table 3. Results of descriptive analysis

Variable	Level	Frequency	Percent	Cumulative percent
Gender	Male	183	47.4	47.4
	Female	203	52.6	100
Age	< 20	32	8.3	8.3
	21-30	65	16.8	25.1
	31-40	37	9.6	34.7
	41-50	41	10.6	45.3
	51-60	107	27.7	73.1
	>60	104	26.9	100
Education	Primary school or lower	53	13.7	13.7
	Secondary school	101	26.2	39.9
	Bachelor’s degree	203	52.6	92.5
	Master’s degree	24	6.2	98.7
	Doctoral degree or higher	5	1.3	100
Income	<10,000	36	9.3	9.3
	10,001-20,000	162	42.0	51.3
	20,001-30,000	168	43.5	94.8
	30,001-40,000	20	5.2	100
	40,001-50,000	0	0	
	>50,000	0	0	
Experience on LINE application	Have	185	47.9	47.9
	None	201	52.1	100

Table 4. Convergent validity and reliability

Latent	Items	Mean	Std.	Loading	Cronbach’s Alpha	CR	AVE
Perceived usefulness	PU1	4.122	0.819	0.896	0.903	0.932	0.775
	PU2	4.277	0.761	0.895			
	PU3	4.307	0.763	0.897			
	PU4	4.034	0.829	0.833			
Perceived ease of use	PEU1	4.206	0.769	0.853	0.871	0.912	0.721
	PEU2	4.084	0.789	0.818			
	PEU3	4.218	0.724	0.873			
	PEU4	4.294	0.720	0.852			
Social norm	SN1	3.794	1.043	0.915	0.928	0.954	0.874
	SN2	3.601	1.110	0.931			
	SN3	3.609	1.097	0.959			
Behavioral intention	BI1	4.122	0.787	0.863	0.845	0.896	0.684
	BI2	4.185	0.756	0.863			
	BI3	4.097	0.837	0.741			
	BI4	3.996	0.862	0.835			

Table 5. Discriminant validity

Latent	VIF	Fornell-Larcker				HTMT			
		Int	PEU	PU	SN	Int	PEU	PU	SN
BI		0.827							
PEU	2.267	0.754	0.849			0.874			
PU	2.225	0.746	0.732	0.881		0.845	0.819		
SN	1.303	0.513	0.457	0.440	0.935	0.576	0.510	0.476	

4.3. Structured equation modelling analysis and hypothesis testing

This study illustrated the appropriate model based on TAM by testing three structural models as presented in Table 6; i) TAM, ii) the TAM extension with social norm as an exogenous variable, and iii) two moderator variables (problematic BMI and technology experience) on TAM which extended social norm as exogenous variable. The results of this study agreed and expanded upon the findings of others [3], [6], [7] even though some previous studies in healthcare context did not suggest a significant relationship in TAM [8], [9], [15]. The first possible reason could be the different technologies. For new technologies such as blockchain [14] and robotic therapy [9], user will feel anxious in terms of security and trust. In contrast, the technology of this study was LINE OA which most Thai people are very familiar with and therefore had no anxiety about its usage. The second explanation involves different sample groups. 67.2% of samples in [9] were less than 46 years old, while 65.3% of samples in this study were greater than 41 years old. Luciani *et al.* [9] stated that PU indicates significant effects on BI in their work and explained the possible reason with relatively young samples.

Table 6. Model comparison

Model	Beta	S.E.	R^2	R^2 Adjust	f^2	Total effect	Q^2
Model 1: TAM							
PU-BI	0.419***	0.069			0.234	0.419***	
PEU-BI	0.448***	0.069	0.650	0.647	0.264	0.755***	0.562
PEU-PU	0.733***	0.039	0.537	0.535	1.158	0.734***	0.528
Model 2: TAM & SN							
PU-BI	0.381***	0.064			0.198	0.382***	
PEU-BI	0.403***	0.071	0.670	0.665	0.214	0.680***	0.593
PEU-PU	0.734***	0.039	0.537	0.535	1.158	0.732***	0.528
SN-BI	0.159**	0.051			0.061	0.162**	
Model 3: TAM & SN & 2 Moderator Variable2 (Technology experience and problematic BMI)							
PU-BI	0.362**	0.138			0.054	0.362***	
PEU-BI	0.443*	0.164	0.692	0.679	0.044	0.706***	0.536
PEU-PU	0.734***	0.039	0.537	0.535	1.158	0.734**	0.528
SN-BI	0.362*	0.122			0.028	0.309*	
Expe-BI	0.309	0.082			0.001	-0.043	
BMI-BI	-0.043	0.090			0.005	0.101	
MOD: Expe[PEU-BI]	0.101*	0.089			0.022	-0.192*	
MOD: Expe[SN-BI]	-0.192	0.107			0.010	0.132	
MOD: BMI[PU-BI]	-0.028	0.157			0.001	-0.028	
MOD: BMI[SN-BI]	-0.249*	0.110			0.020	-0.249*	

Note: * is p-value<0.05, ** is p-value<0.01, and *** is p-value<0.001

Therefore, the findings of this study are reasonable. Additionally, a significant association was found between social norm and behavioral intention to use technology, as with the other prior literature in healthcare context [9], [17]. A possible explanation was the features of social media. LINE OA is a social media technology, and society will influence behavioral intention to use information technology. Therefore, the social norm should be an extended factor in TAM, to better understanding customer behavioral intention to use IT in healthcare context.

Furthermore, the study revealed the role of problematic BMI as a moderating variable. The findings suggested that problematic BMI influences the relationship between the social norm and customer behavioral intention to use IT in the healthcare context, especially the customer group in problematic BMI. One possible explanation is that problematic BMI customers frequently upload their meal photos and changes in body weight, supported preliminary findings [26]. In contrast, our results present an insignificant role of problematic BMI in association with perceived usefulness and customer behavioral intention to use IT. One possible reason is that HC-HS provided the healthcare information to serve customer needs in both groups (with or without problematic BMI). As a result, problematic BMI did not have a different impact to people with us without problematic BMI.

Finally, the findings illustrated the impact of technology experience as significant moderating variable of the relation between perceived ease of use and user’s behavioral intention to use IT, this confirmed UTAUT [12] in healthcare context. In addition, this confirmed to previous works [18], [19], which indicated changed learning skills at different levels of technology experience. However, the result showed that technology experience did not impact on the relationship between social norm and behavioral intention, thus technology experience cannot be a moderator on association of social norm and behavioral intention. This finding differed from the UTAUT results [12]. One reason could be that Thai people are very familiar with the usage of LINE OA. Therefore, the differing technology skills had no impact on their social norm towards behavioral intention to use technology. After revising insignificant paths, the proposed model for user acceptance towards information technology in healthcare context was adapted as shown in Figure 4. This model can be applied in furthering research and developing programs.

From a practical standpoint, social influence has an important impact on users’ behavioral intention to use information technology in healthcare context. Therefore, healthcare businesses and developers may consider society and social communication in new designs of healthcare information services, as well as optimizing existing IT interfaces and functions to improve user services by content sharing, group creating, and user reviews. In addition, the moderating role of problematic BMI indicated the importance of the relationship between social influence and user's behavioral intention to use IT. Hence, to attract users with a problematic BMI, healthcare businesses and developers should provide useful instructions in terms of problematic BMI and BMI calculation. Furthermore, the findings revealed the important role of technology experience on the relationship between perceived ease of use and user's behavioral intention to use IT. Therefore, to appeal to those with low technology experience, healthcare businesses and developers should provide IT services based on ease for self-learning, technology usage, and demo clips. This finding can be applied to general health services using social media technology as well.

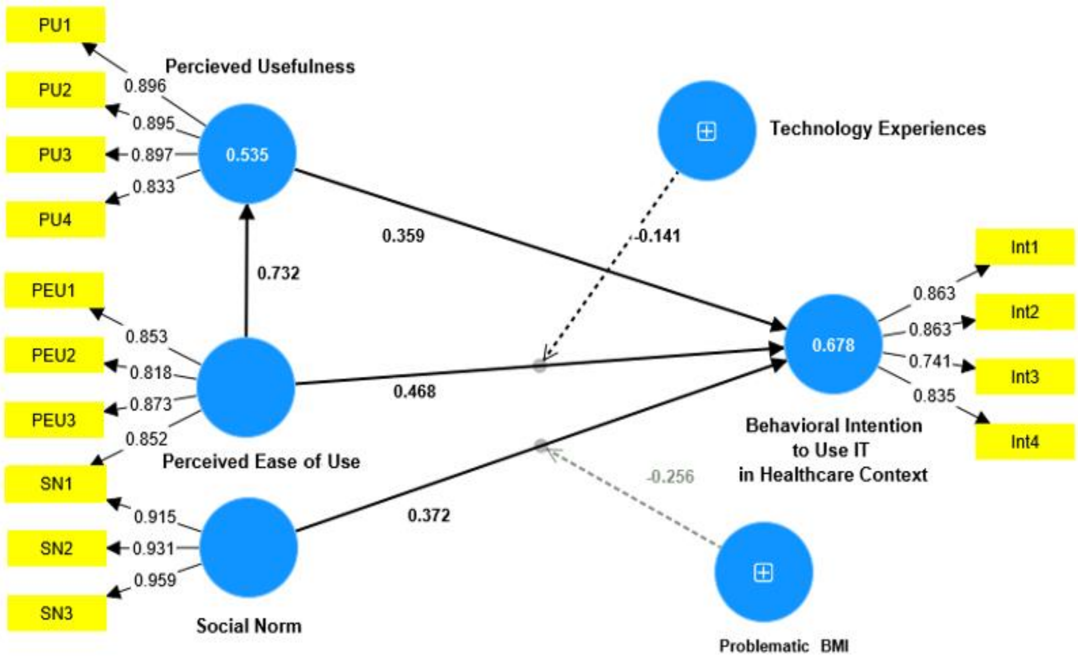

Figure 4. The proposed model for healthcare business after revision

5. CONCLUSION

In conclusion, this study revealed important factors of customer intention to use TAM-based information technology in the healthcare context. The findings confirmed the original TAM that perceived usefulness and perceived ease of use as basic factors on customer intention to use information technology. Furthermore, the social norm should be extended to TAM as the independent variable, and problematic BMI and technology experience should be extended as moderator variables in healthcare context. The findings provided actionable insights into developing effective healthcare services using information technology, especially for technology-experienced customers with problematic BMI.

The proposed model was developed to illustrate the emergent factors in this study, that do not include all factors of the user's behavioral intention to use IT (R^2=0.692). Future research may explore other possible factors in the proposed model to enhance the understanding of user's behavioral intention towards the technology use. Finally, the limitations of technology should be considered in future research. As a result of some disagreement between findings and literature reviews, the proposed model may not be explained in some technologies other than information technology, such as robotics and hardware devices.

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