

An Investigation on Behavioral Intention toward Usage of Personal Health Assistant Service and Technology Among Patients in Bangkok, Thailand

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Abstract

Purpose: The study aims to investigate the determinants of behavioral intention toward the usage behavior of personal health assistant services and technology for hypertension patients of a private hospital in Bangkok. Eight variables conform to the conceptual framework, including perceived usefulness, perceived ease of use, attitude toward using, customer satisfaction, social influence, facilitating condition, behavioral intention, and usage behavior. **Research design, data, and methodology:** The data were collected from 500 participants. The sampling techniques used were purposive, stratified random, and convenience samplings. Before collecting the data, the index of item objective congruence (IOC) and Cronbach's Alpha coefficient value (pilot testing) of 50 samples were applied. The main statistical approaches involve confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results:** Perceived usefulness has a significant influence on attitude toward use. Attitude toward use has a significant influence on customer satisfaction and behavioral intention. Social influence and facilitating conditions significantly influence behavioral intention. In addition, behavioral intention significantly influences use behavior. On the other hand, perceived ease of use does not significantly influence attitudes toward using personal healthcare assistant services. **Conclusions:** Healthcare service providers can enhance the purchase intention of digital healthcare technology, which could remarkably benefit patients by tracking and monitoring their health conditions.

Keywords: Customer Satisfaction, Social Influence, Facilitating Condition, Behavioral Intention, Usage Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In 2021, Thailand's health tech market showed moderate spending power at an estimated THB 300 to 400 million. The Covid-19 pandemic has rapidly accelerated health services technology to decrease risk and offer better convenience to patients remotely. Furthermore, Thailand is entering the "aged society," and people tend that prefer

"preventive health behaviors," which tends to open the door for the health innovation and technology market to grow remarkably (KResearch, 2021).

Personal or virtual health assistant technology has remarkably received wide attention in most businesses to improve their market efficiency and satisfy customers. System technology can meet detour requirements or customer inquiries and save up 78 percent in operating costs

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annually. Some statistics highlight the significant effect of personal health assistant technology in the healthcare market in Thailand. A virtual assistant enquires about some investment costs and lead time of the system's adoption. The tangible assets may not be much seen, such as office equipment to run the program of a virtual assistant system, but hidden costs incur developers, servers, etc. Examples are remote call centers, telemedicine, virtual consultants, and many more (Delegated, 2020).

Healthcare businesses have evolved dramatically even before the time of the global pandemic. Most health systems and technology have been developed following new investment trends, an aging society, chronic health conditions, upgraded technologies, and talent development. Numerous challenges have been addressed with incomplete solutions, such as insufficient knowledge, complicated technology, misplaced data, etc. Digital transformation unleashes the power of system technology for innovative products/services, continuous improvement processes, and vice versa.

In the rise of the health tech market in Thailand, this research aims to respond to the market growth and consumer demand for personal/virtual health assistant services and technology—many startups in Thailand gear towards building virtual technology in responding to Covid-19 disruption. The pandemic has accelerated the growth of digital health technologies, which opens opportunities for health tech service providers and developers. The study aims to investigate the determinants of behavioral intention toward using personal health assistant services and technology for hypertension patients in a private hospital in Bangkok. Eight variables conform to the conceptual framework, including perceived usefulness, perceived ease of use, attitude toward using, customer satisfaction, social influencing, facilitating condition, behavioral intention, and usage behavior.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is a key factor of the technology acceptance model (TAM), which narrates an individual's process of using a particular technology (Davis, 1989). Perceived usefulness refers to “the potential user's possible that using a specific system or technology will increase his or her job performance within an organizational context” (Davis et al., 1989). In healthcare, TAM has widely included perceived usefulness as a significant determinant in explaining a user's intention to use an application system (Holden & Karsh, 2010).

TAM presents potential technology adoption

determinants, inhibiting the significant relationship between perceived usefulness and attitude toward using a technology (Didyasarini et al., 2017; Lin & Chang, 2011). TAM also helps most researchers better understand users' usage behavior in the acceptance of technology. Davis (1989) explained that when people believe technology usage could provide benefits, they would have a positive feeling or confidence to use it. Therefore, perceived usefulness can be a potential driver of attitude toward use (Baron & Banaji, 2006; Fishbein & Ajzen, 1975). Hence, this study proposed: **H1:** Perceived usefulness has a significant influence on attitude toward using personal healthcare assistant service.

2.2 Perceived Ease of Use

TAM has been commonly used to predict technology acceptance among users for decades (To & Tang, 2019). Davis (1989) mentioned that a key factor affecting users' behavioral intention of using a particular innovation or technology is “perceived ease of use,” which is defined as “the degree to which individuals believe that using technology is free of effort” Venkatesh et al. (2003) extended that perceived ease of use is similar to effort expectancy of UTAUT model. To determine the intentional behavior and usage behavior, perceived ease of use can drive users' perception of the usefulness of technology (Davis, 1989).

Many scholars noted that perceived ease of use is a key influencing factor that drives attitude toward using a technology (Childers et al., 2001; Didyasarini et al., 2017; Lin & Chang, 2011; Nysveen et al., 2005; Robinson et al., 2005). The high degree of ease of use raises the positive attitude toward technology use (Kleijnen et al., 2004). Davis et al. (1989) also explained the perceived ease of use as an individual's belief that using technology is easy and requires minimum effort, which can develop a positive feeling toward the usage. Thus, perceived ease of use significantly impacts attitudes toward using technology, as supported by many studies. Based on previous studies, a hypothesis was set:

H2: Perceived ease of use has a significant influence on attitude toward using personal healthcare assistant service.

2.3 Attitude Toward Using

Many definitions term attitude. Abate (1999) noted attitude as a “settled opinion.” Venes (2001) defined it as “a behavior based on conscious or unconscious mental views developed through cumulative experience” In the healthcare context, attitude can be perceived by a person when he or she experiences medical care and other relevant services where own's evaluation could determine a specific item whether it meets their needs and expectation (Zeithaml et al.,

2006). Ajzen and Fishbein (1980) posited that attitude toward using technology is an assessment of whether customers have a positive or negative feeling towards it.

Attitude toward using is an assessment of whether customers have positive or negative feelings about using technology (Ajzen & Fishbein, 1980). Attitude is a cognitive state of mind among users or customers, which plays a key role in driving intentional behavior to use a technology or to purchase a product/service (Ajzen & Fishbein, 1980). It also explains a person's positive or negative feelings in performing a particular behavior (Yuan et al., 2021).

Consumers with positive attitudes about the technology will be driven by such intrinsic emotion to build behavioral intention to use it. Thus, a significant relationship between attitude toward the use and behavioral intention is attained (Dabholkar & Bagozzi, 2002). Besides, users with favorable attitudes tend to express readiness and willingness to engage with technology if they believe it could serve their goals (Kleijnen et al., 2004). As a result, the relationship between attitude toward using and behavioral intention to use personal health assistance services can comply with those arguments. Hence, two hypotheses were set:

H3: Attitude toward use has a significant influence on customer satisfaction on personal healthcare assistant service.

H4: Attitude toward using has a significant influence on behavioral intention of personal healthcare assistant service.

2.4 Customer Satisfaction

Customers evaluate a product or service and whether it meets their needs and expectation, and such a judgment can be clarified as the level of satisfaction (Zeithaml et al., 2006). Customer satisfaction expresses emotional judgment related to previous experience or the latest consumption of products and services. In addition, the degree of customer satisfaction can build a repurchase intention and positive recommendation to prospective customers. In healthcare, customers are patients who receive medical and nursing care from healthcare service providers such as clinics or hospitals (Didyasarin et al., 2017). In marketing study, the satisfaction procedure is critical to designing sales and marketing strategies to achieve sales revenue (Kandampully & Suhartanto, 2000). A satisfied customer can be easier to retain than a dissatisfied one. Thus, most organizations invest time and effort to measure the satisfaction of their customers (Choi & Kim, 2011) and to maximize profit and organizational performance (Barsky & Nash, 2003).

2.5 Social Influence

Social influence is “the degree to which an individual perceives those important persons’ believe they should use

the new system.” Social influence explains a behavioral process that involves other persons’ influence on an individual’s attitudes and actions (Stibe, 2015; Venkatesh et al., 2003). Other persons can dominate and refer to an individual’s use of new technology. It is a persuasive format that motivates users to try a system or technology. The influencers can be family, friends, peers, and colleagues who can encourage a person to perform a behavior (Haslam et al., 1996) and potentially affect the use of a new system (Alraja, 2015).

Social influence has been referred to as a belief of a person in the importance of others that he/she could decide to perform certain behaviors (Venkatesh et al., 2003). According to the original UTAUT model, social influence is a key construct that drives behavioral intention towards an actual use of technology. Social influence significantly impacted behavioral intention in mobile health services (Sun et al., 2013). Pan and Jordan-Marsh (2010) claimed that there was a direct correlation between social influence and behavioral intention to use technology among elderly participants. Developing from the support literature, the following hypothesis was obtained:

H5: Social influence has a significant influence on behavioral intention of personal healthcare assistant service.

2.6 Facilitating Condition

Facilitating condition is “the degree to which a person believes that the existing organizational and technical infrastructure can support the use of technology” (Chan et al., 2010). The UTAUT model builds a facilitating condition to predict behavioral intention toward use behavior (Venkatesh et al., 2003). Facilitating conditions is associated with the accessibility of adequate resources and facilitating the use of technology by individuals (Neslin & Shankar, 2009). Insufficient support, such as information, time, and budget, could block or reduce individuals’ chances of adopting a particular system (Kamaghe et al., 2020). In an online context, the internet, software, and hardware infrastructure have viewed as important to the adoption process (Lee, 2017).

Facilitating condition explains a belief that an individual using technology would receive the necessary infrastructure from a service provider (Venkatesh et al., 2003). Facilitating conditions can produce a behavioral intention to use a system because a user expects adequate to support such as devices, internet connection, training, or maintenance support from a company that introduces such technology. In healthcare technology, numerous literatures confirmed that behavioral intention is influenced by facilitating conditions in health technology system (Aggelidis & Chatzoglou, 2009), smartphones for health services (Boontarig et al., 2012), and mobile health services (Alam et al., 2020;

Cimperman et al., 2016). Subsequently, the above reports produced a following hypothesis:

H6: Facilitating condition has a significant influence on behavioral intention of personal healthcare assistant service.

2.7 Behavioral Intention

Behavioral intention is an essential variable of well-known technology adoption models such as TAM and UTAUT (Venkatesh et al., 2012). It refers to “a person’s level of intention to use technology” (Budu et al., 2018). The behavior intention can greatly contribute to usage behavior. Therefore, behavioral intentions are key for social and business researchers to understand the process customers involve in deciding on purchasing a product/service or using technology. Tran (2020) urged that relationship quality significantly impacts experience and behavioral intention. Additionally, the frequency of technology usage predicts intentional behavior for the future adoption of a system (Al-Rahmi et al., 2019). Three behavior indicators include intention, habits, and usage interest (Venkatesh et al., 2012).

According to Venkatesh et al. (2003), the UTAUT model offers the technology adoption model with influencing factors contributing to behavioral intention towards usage behavior. Similarly, some studies investigated TAM with behavioral intention as a strong predictor of usage behavior in several technologies and services. During the pandemic, where most organizations are strongly recommended to replace technology to ensure a smooth personal service experience instead of face-to-face interaction, technology adoption has been largely deployed in various business areas (Egan et al., 2004). Developing from the support literature, the following hypothesis is obtained:

H7: Behavioral intention has a significant influence on usage behavior of personal healthcare assistant service.

2.8 Usage Behavior

The usage behavior is constructed in most technology adoption models. TAM and UTAUT have been widely accepted to examine the successful adoption of a particular technology. Usage behavior determines the final goal to complete the user’s decision-to-action cycle: to use a specific system, innovation, and technology (Davis, 1989; Venkatesh et al., 2003). Use behavior has been commonly framed as a dependent variable because it depends on measuring the behavioral intention of both TAM and UTAUT models. Usage behavior is commonly derived from TAM, which is strongly affiliated with perceptions, attitudes, and willingness to use (Fishbein & Ajzen, 1975). In previous literature, Zhong et al. (2022) conceptualized behavioral intention to use an online learning system.

3. Research Methods and Materials

3.1 Research Framework

A conceptual framework was developed from four research models in the healthcare services context. The previous studies determined the adoption of personal health assistant services per the research topic. The previous studies are Lin and Chang (2011), Didyasarini et al. (2017), Moudud-Ul-Huq et al. (2021), and Barua and Barua (2021). Consequently, this study developed a conceptual framework shown in Figure 1.

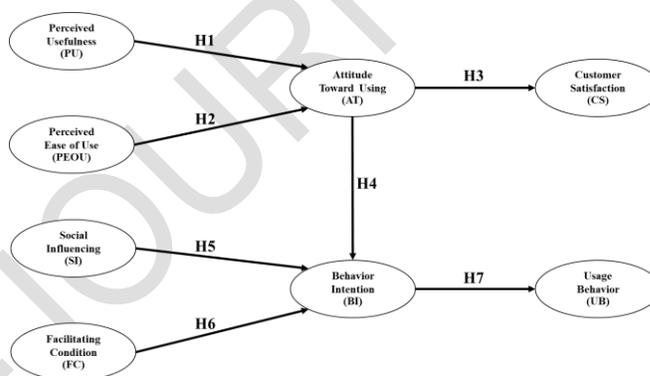


Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant influence on attitude toward using personal healthcare assistant service.

H2: Perceived ease of use has a significant influence on attitude toward using personal healthcare assistant service.

H3: Attitude toward use has a significant influence on customer satisfaction on personal healthcare assistant service.

H4: Attitude toward using has a significant influence on behavioral intention of personal healthcare assistant service.

H5: Social influence has a significant influence on behavioral intention of personal healthcare assistant service.

H6: Facilitating condition has a significant influence on behavioral intention of personal healthcare assistant service.

H7: Behavioral intention has a significant influence on usage behavior of personal healthcare assistant service.

3.2 Research Methodology

The study aims to investigate the determinants of behavioral intention toward using personal health assistant services and technology for hypertension patients at a private hospital in Bangkok. Formerly to the data gathering, the index of item objective congruence (IOC) and Cronbach’s Alpha coefficient value (pilot testing) of 50 samples were

confirmed. The survey consists of three parts, screening questions, measuring items Five-point Likert scale, and demographical profiles, including gender, nationality, age group, education, and occupation. The statistical approaches involve confirmatory factor analysis (CFA) and structural equation modeling (SEM).

3.3 Validity and Reliability

Validity describes “how well the collected data covers the actual area of investigation” (Ghauri & Gronhaug, 2005). IOC is “an application in which experts score each research instrument based on the degree to which they measure specific objectives listed by the test developer” (Hambleton et al., 1978). All experts were requested to rate the score. Consequently, all 30 items remained at the score of 0.67 and above and were unnecessary to be revised. This study targeted 50 samples with the use of Cronbach’s Alpha. The acceptable value of coefficient value should be equal to or above 0.60, as recommended by Hair et al. (2003).

3.4 Population and Sample Size

This study aims to investigate the behavioral intention toward using personal health assistant services and technology among hypertension patients of Bumrungrad International Hospital in Bangkok, Thailand. Hypertension patients have a high blood pressure level of 140-159 and/or 90-99, very high level is 160-179 and/or 100-109, and an extreme level is <180 and/or >110. Therefore, the target population of this study is hypertension patients of Bumrungrad Hospital. The online statistical software based on the prior sample size calculator for structural equation models the minimum sample size by Soper (2022) estimates the minimum sample size of 444 samples. Accordingly, 500 samples are appropriate for the SEM analysis.

3.5 Sampling Technique

This study applied probability sampling and non-probability sampling methods in generalizing in three steps: purposive sampling, stratified random sampling, and convenience sampling. Purposive sampling is to select qualified participants who are hypertension patients of Bumrungrad Hospital. From Table 1, stratified random sampling is based on four groups of generations; 40-49 (Generation Y), 50-59 (Generation X), 60-69 (Baby Boomer), and 70 and Up (Senior Citizen). The research employed convenience sampling to distribute electronic and paper questionnaires to the qualified participants via MS Form.

Table 1: Stratified Random Sampling

Year-Old Range	Total number of Hypertension and Potential to have Hypertension Symptoms Patients	Hypertension Symptoms	Population Size of existing patients in Hypertension
Generation Y	7,473	4,832	102
Generation X	7,980	6,124	130
Baby Boomer	6,683	6,025	128
Senior Citizen	6,822	6,633	140
Total	28,958	23,614	500

Source: Constructed by Author (Based on the data from Bumrungrad International Hospital).

4. Results and Discussion

4.1 Demographic Information

The demographic results from 500 participants show that males are 49 percent and females are 51 percent. Thai patients are 62.8 percent, and non-Thai patients are 37.2 percent. Most respondents are 70 and up at 28 percent, 50-59 years old at 26 percent, 60-69 years old at 25.6 percent, and 40-49 years old at 20.4 percent. Bachelor’s degree takes the largest group of 64.8 percent. For occupation, most respondents are corporate employees at 29.6 percent, followed by entrepreneur/ business owners at 25 percent, and government officials at 17.8%.

Table 2: Demographic Profile

Demographic and General Data (n=500)		Frequency	Percentage
Gender	Male	245	49.0%
	Female	255	51.0%
Nationality	Thai	314	62.8%
	Non-Thai	186	37.2%
Age	40-49 Years Old	102	20.4%
	50-59 Years Old	130	26.0%
	60-69 Years Old	128	25.6%
	70 Years Old and Up	140	28.0%
Education	Below Bachelor’s Degree	55	11.0%
	Bachelor’s degree	324	64.8%
	Master’s degree	76	15.2%
	Doctor’s degree	45	9.0%
Occupation	Government Officer	89	17.8%
	Corporate Employee	148	29.6%
	Entrepreneur/ Business Owner	125	25.0%
	Workers	86	17.2%
	Househusbands/ Housewives	32	6.4%
	Retirement	12	2.4%
	Others	8	1.6%

4.2 Confirmatory Factor Analysis (CFA)

According to Table 3, CFA's results are determined by factor loadings equal to or above 0.50 and a p-value lower than 0.05. The acceptable coefficient value should be equal

to or above 0.60, as Hair et al. (2003) recommended. Furthermore, the Composite Reliability (CR) is greater than the cut-off points of 0.6, and Average Variance Extracted (AVE) is higher than the cut-off point of 0.4 (Fornell & Larcker, 1981).

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Usefulness (PU)	Nysveen et al. (2005)	3	0.771	0.715-0.751	0.772	0.531
Perceived Ease of Use (PEOU)	Nysveen et al. (2005)	4	0.778	0.587-0.801	0.780	0.473
Attitude Toward Using (AT)	Nysveen et al. (2005)	4	0.788	0.620-0.770	0.793	0.492
Customer Satisfaction (CS)	Leppäniemi et al. (2017)	5	0.808	0.608-0.720	0.814	0.467
Social Influencing (SI)	Moudud-UI-Huq et al. (2021)	3	0.894	0.846-0.881	0.894	0.738
Facilitating Condition (FC)	Moudud-UI-Huq et al. (2021)	4	0.782	0.672-0.726	0.783	0.475
Behavior Intention (BI)	Moudud-UI-Huq et al. (2021)	3	0.889	0.821-0.900	0.888	0.725
Usage Behavior (UB)	Venkatesh et al. (2012) and Taylor and Todd (1995)	4	0.793	0.678-0.723	0.793	0.490

The measurement model is used to assess the association among the observed constructs, identified as indicators, and unobserved constructs, applying in factor analysis. According to Table 4, the goodness of fit indices of the measurement model in the CFA is an acceptable fit, including CMIN/DF = 1.325, GFI = 0.937, AGFI = 0.922, NFI = 0.930, CFI = 0.982, TLI = 0.979, IFI = 0.982, and RMSEA = 0.026.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	499.551/377 = 1.325
GFI	≥ 0.85 (Kline, 2011)	0.937
AGFI	≥ 0.85 (Kline, 2011)	0.922
NFI	≥ 0.85 (Kline, 2011)	0.930
CFI	≥ 0.85 (Kline, 2011)	0.982
TLI	≥ 0.85 (Kline, 2011)	0.979
IFI	≥ 0.85 (Kline, 2011)	0.982
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.026
Model summary		Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

Source: Created by the author.

Hair et al. (2014) referred to discriminant validity as the extent to which the construct differs empirically and measures the degree of differences between the overlapping construct. In Table 5, the values show that discriminant validity is larger than all inter-construct/factor correlations. Consequently, the discriminant validity is approved.

Table 5: Discriminant Validity

	CS	PU	AT	BI	UB	PEOU	SI	FC
CS	0.683							
PU	0.643	0.729						
AT	0.679	0.550	0.702					
BI	0.669	0.543	0.582	0.852				
UB	0.364	0.301	0.474	0.442	0.700			
PEOU	0.252	0.306	0.246	0.314	0.177	0.688		
SI	0.619	0.529	0.504	0.756	0.407	0.285	0.859	
FC	0.616	0.524	0.631	0.683	0.634	0.302	0.616	0.689

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

A path diagram is built to frame the hypnotized model. The observed and latent construct present the structural pathway of the relationship in a model (McDonald & Ho, 2002). Based on Table 6, the results show the structural model fit in this study after adjustment with CMIN/DF = 1.705, GFI = 0.918, AGFI = 0.902, NFI = 0.906, CFI = 0.959, TLI = 0.954, IFI = 0.959, and RMSEA = 0.038.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values	
		Before Adjustment	After Adjustment
CMIN/DF	< 3.00 (Hair et al., 2006)	1110.625/398 = 2.791	666.664/391 = 1.705
GFI	≥ 0.85 (Kline, 2011)	0.864	0.918
AGFI	≥ 0.85 (Kline, 2011)	0.841	0.902
NFI	≥ 0.85 (Kline, 2011)	0.843	0.906

Index	Acceptable Values	Statistical Values	
		Before Adjustment	After Adjustment
CFI	≥ 0.85 (Kline, 2011)	0.893	0.959
TLI	≥ 0.85 (Kline, 2011)	0.883	0.954
IFI	≥ 0.85 (Kline, 2011)	0.894	0.959
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.060	0.038
Model summary		Unacceptable Model Fit	Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

Source: Created by the author.

4.4 Research Hypothesis Testing Result

The summary in Table 7 shows that the seven proposed hypotheses are proved by structural equation modeling (SEM), examined by the standardized path coefficient value (β), t-value, and p-value <0.05 is a measure of the significant effect.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→ATT	0.758	10.202*	Supported
H2: PEOU→ATT	0.059	1.168	Not Supported
H3: ATT→CS	0.825	10.858*	Supported
H4: ATT→BI	0.210	5.035*	Supported
H5: SI→BI	0.636	13.457*	Supported
H6: FC→BI	0.185	3.871*	Supported
H7: BI→UB	0.473	8.804*	Supported

Note: * p<0.05

According to Table 7, this study can be further discussed:

H1 confirms that perceived usefulness significantly influences attitudes toward using personal healthcare assistant services, reflected in the standardized path coefficient value of 0.758 (t-value = 10.202). The technology adoption model presents a significant relationship between perceived usefulness and attitude toward technology use (Didiyasarin et al., 2017; Lin & Chang, 2011).

H2 presents a standardized path coefficient value of 0.059 (t-value = 1.168), which fails to support the relationship between perceived ease of use and attitude toward using. The results of this study oppose Kleijnen et al. (2004), who addressed that the high degree of ease of use potentially raises the positive attitude toward using

technology.

H3 shows that attitude toward use significantly influences customer satisfaction, revealing the standardized path coefficient value of 0.825 (t-value = 10.858). Yuan et al. (2021) explained that a person’s feelings are either positive or negative in performing a particular behavior.

H4 approves the significant impact of the attitude and behavioral intention, representing a standardized path coefficient value of 0.210 (t-value = 5.035). Consumers with positive attitudes drive behavioral intention to use new technology (Dabholkar & Bagozzi, 2002).

H5 supports the significant relationship between social influence and behavioral intention, resulting in a standardized path coefficient of 0.636 (t-value = 13.457). Social influence significantly impacted behavioral intention in mobile health services (Sun et al., 2013).

H6 verifies the significant relationship between facilitating conditions and behavioral intention with a standardized path coefficient of 0.185 (t-value = 3.871). Facilitating condition explains a belief of a patient to use technology for better (Venkatesh et al., 2003).

H7 verifies that behavioral intention significantly influences the usage behavior of personal healthcare assistant service with a standardized path coefficient of 0.473 (t-value = 8.804). According to Venkatesh et al. (2003), the technology adoption model can determine that behavioral intention significantly influences usage behavior.

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

The findings serve the research aim to examine the significant relationship of key variables. The study aims to investigate the determinants of behavioral intention toward the usage behavior of personal health assistant services and technology for hypertension patients in a private hospital in Bangkok. The statistical results from CFA and SEM show that perceived usefulness significantly influences attitudes toward use. Attitude toward use has a significant influence on customer satisfaction and behavioral intention. Social influence and facilitating conditions significantly influence behavioral intention. In addition, behavioral intention significantly influences use behavior. On the other hand, perceived ease of use does not significantly influence attitudes toward using personal healthcare assistant services.

Based on the data collected from 500 hypertension patients of Bumrungrad International Hospital in Bangkok, Thailand, perceived usefulness significantly influences attitudes toward use. Davis (1989) acknowledged that when people believe technology usage could provide benefits, they would have a positive attitude toward it. Ajzen and

Fishbein (1980) theorize that attitude as a cognitive state of mind of patients would play a key role in driving satisfaction and intentional behavior to use a technology or to purchase a product/service.

Furthermore, Sun et al. (2013) indicated that social influence is a key construct that drives behavioral intention toward using technology. This can determine how patients would be dominated by other significant and opinion leaders to use personal healthcare assistant services. Aggelidis and Chatzoglou (2009) reported that behavioral intention is influenced by facilitating conditions in the health technology system. Healthcare service providers offer innovative tools for patients to track their hypertension.

Nevertheless, perceived ease of use does not significantly influence attitudes toward using personal healthcare assistant services, but it is directly related. Even the high degree of ease of use of personal healthcare assistant services can predict the attitude toward the use, but it is not significantly related (Kleijnen et al., 2004). The results oppose Davis et al. (1989) that users develop an attitude that is influenced by perceived ease of use.

5.2 Recommendation

The recommendations are based on the theories and results of the research. In order to encourage the positive attitude of patients, healthcare service providers need to assess the need and solutions to their problems. In light of this, personal healthcare assistant services must enhance the quality of treatment and other means of health for patients. The benefits of personal healthcare assistant services should be communicated to the patients on how it could be the tools or solution for their health concerns.

Personal healthcare assistant services require the ease of use of the technology that would deliver. Therefore, patients would evaluate the service through it is easy to understand and use. The evaluation of patients can lead to a positive attitude that enhances satisfaction and behavioral intention to use. Therefore, health tech developers should examine patients' needs relative to the tools' design that meet users' expectations.

Social influence can be either through close relationships or through media. Personal healthcare assistant services can be endorsed by users to other users on how they use them and the benefits that they have been offered. The media could be through advertising by own, paid, or earned media such as hospitals' websites, influencers, and product/service reviews. Facilitating conditions can be in the form of download applications, wearable devices, or other related software. Behavioral intention can arouse the use behavior; therefore, the patient should consult with healthcare service personnel about the information of such personal healthcare assistant services.

5.3 Limitation and Further Study

The limitations for the future can be discussed. First, this research focused on a group of patients in a private hospital in Thailand. The future study should extend to other regions or hospital types. Second, the conceptual framework is limited to eight variables: perceived usefulness, perceived ease of use, attitude toward using, customer satisfaction, social influencing, facilitating condition, behavioral intention, and usage behavior. Hence, the conceptual framework, such as trust, service quality, and word of mouth, can be extended. Third, this study applied quantitative methods. Therefore, the qualitative should be extended.

References

- Abate, F. R. (1999). *The Oxford American dictionary of current English* (1st ed.). Oxford University.
- Aggelidis, V. P., & Chatzoglou, P. D. (2009). Using a modified technology acceptance model in hospitals. *International Journal of Medical Informatics*, 78(2), 115-126.
- Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Prediction Social Behavior*. Prentice-Hall.
- Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: a patient-centric study. *International Journal of Information Management*, 50, 128-143, <https://doi.org/10.1016/j.ijinfomgt.2019.04.016>
- Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating Technology Acceptance Model with Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems. *IEEE Access*, 7, 26797-26809. <https://doi.org/10.1109/ACCESS.2019.2899368>
- Alraja, M. N. (2015). User Acceptance of Information Technology: A field study of an e-mail system Adoption from the Individual students' Perspective. *Mediterranean Journal of Social Sciences*, 6(6), 1-19.
- Baron, A., & Banaji, M. (2006). The Development of Implicit Attitudes. Evidence of Race Evaluations From Ages 6 and 10 and Adulthood. *Psychological science*, 17(1), 53-8. <https://doi.org/10.1111/j.1467-9280.2005.01664.x>
- Barsky, J., & Nash, L. (2003). Customer satisfaction: Applying concepts to industry- wide measures. *The Cornell Hotel and Restaurant Administration Quarterly*, 44(4), 173-183.
- Barua, Z., & Barua, A. (2021). Acceptance and usage of mHealth technologies amid COVID-19 pandemic in a developing country: the UTAUT combined with situational constraint and health consciousness. *Journal of Enabling Technologies*, 15(1), 1-22. <https://doi.org/10.1108/JET-08-2020-0030>
- Boontarig, W., Chutimaskul, W., Chongsuphajsiddhi, V., & Papisratorn, B. (2012). *Factors influencing the Thai elderly intention to use smartphone for e-Health services* [Paper presentation]. IEEE symposium on humanities, science and engineering research.

- Budu, K. W. A., Yiping, M., & Mireku, K. K. (2018). Investigating The Effect of Behavioral Intention on E-learning Systems Usage: Empirical Study on Tertiary Education Institutions in Ghana. *Mediterranean Journal of Social Sciences*, 9(3), 201-216. <https://doi.org/10.2478/mjss-2018-0062>
- Chan, F. K. Y., Thong, J. Y. L., Venkatesh, V., Brown, S. A., Hu, P. J. H., & Tam, K. Y. (2010). Modeling citizen satisfaction with mandatory adoption of an E-Government technology. *Journal of the Association for Information Systems*, 11(10), 519-549. <https://aisel.aisnet.org/jais/vol11/iss10/2>
- Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of Retailing*, 77(4), 511-535.
- Choi, N. H., & Kim, Y. S. (2011). The roles of hotel identification on customer-related behavior. *Nankai Business Review International*, 2(3), 240-256.
- Cimperman, M., Brencic, M. M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior - applying an extended UTAUT model. *International Journal of Medical Informatics*, 90, 22-31.
- Dabholkar, P. A., & Bagozzi, R. P. (2002). An attitudinal model of technology-based self-service: moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science*, 30(3), 184-201.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 318-339.
- Davis, F. D., Bagozzi, R., & Warshaw, P. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35(8), 982-1003. <https://doi.org/10.1287/mnsc.35.8.982>
- Delegated. (2020, May 15). *Virtual Assistant Statistics You Need to Pay Attention To in 2020*. <https://www.delegated.com/blog/virtual-assistant-statistics>
- Didyasarini, H., Vongurai, R., & Inthawadee, S. (2017). The factors impact attitude toward using and customer satisfaction with elderly health care mobile application services: a case study of people in Bangkok metropolitan, Thailand. *AU-GSB E-JOURNAL*, 10(1), 167-176. <http://www.assumptionjournal.au.edu/index.php/AU-GSB/article/view/2870>
- Egan, T. M., Yang, B., & Bartlett, K. R. (2004). The effects of organizational learning culture and job satisfaction on motivation to transfer learning and turnover intention. *Human Resource Development Quarterly*, 15(3), 279-301. <https://doi.org/10.1002/hrdq.1104>
- Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research* (1st ed.). Addison-Wesley.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.2307/3151312>
- Ghauri, P., & Gronhaug, K. (2005). *Research Methods in Business Studie* (4th ed.). FT/Prentice Hall.
- Hair, J. F., Babin, B., Money, A. H., & Samouel, P. (2003). *Essential of business research methods* (3rd ed.). John Wiley & Sons.
- Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate Data Analysis* (6th ed.). Pearson Education.
- Hair, J., Hult, T., Ringle, C., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd ed.). Sage Publications.
- Hambleton, R. K., Swaminathan, H., Algina, J., & Coulson, D. B. (1978). Criterion-referenced testing and measurement: A review of technical issues and developments. *Review of Educational Research*, 48(1), 1-47. <https://doi.org/10.2307/1169908>
- Haslam, S. A., McGarty, C., & Turner, J. C. (1996). Salient group memberships and persuasion: The role of social identity in the validation of beliefs. In J. L. Nye & A. M. Brower (Eds.), *What's social about social cognition? Research on socially shared cognition in small groups* (pp. 29-56). Sage Publications. <https://doi.org/10.4135/9781483327648.n2>
- Holden, R. J., & Karsh, B. T. (2010). Methodological Review: The Technology Acceptance Model: Its past and its future in health care. *Journal of Biomedical Informatics*, 43(1), 159-172. <https://doi.org/10.1016/j.jbi.2009.07.002> PMID:19615467
- Kamaghe, J., Luhanga, E., & Kisangiri, M. (2020). The challenges of adopting M-learning assistive technologies for visually impaired learners in higher learning institution in Tanzania. *International Journal of Emerging Technologies in Learning*, 15(1), 140-151. <https://doi.org/10.3991/ijet.v15i01.11453>
- Kandampully, J., & Suhartanto, D. (2000). Customer loyalty in hotel industry: the role of customer satisfaction and image. *International Journal of Contemporary Hospitality Management*, 12(6), 346-351.
- Kleijnen, M., Wetzels, M., & de Ruyter, K. (2004). Consumer acceptance of wireless finance. *Journal of Financial Services Marketing*, 8(3), 206-217.
- Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). The Guilford Press.
- KResearch. (2021, July 14). *Growth potential for health tech in Thailand amid rising demand for health services (Current Issue No.3243)*. <https://www.kasikornresearch.com/en/analysis/k-econ/business/Pages/Health-Tech-z3243.aspx>
- Lee, J. W. (2017). Critical Factors Affecting Consumer Acceptance of Online Health Communication: An Application of Service Quality Models. *Journal of Asian Finance, Economics and Business*, 4(3), 85-94. <https://doi.org/10.13106/jafeb.2017.vol4.no3.85>
- Leppäniemi, M., Jayawardhena, C., Karjaluoto, H., & Harness, D. (2017). Unlocking behaviors of long-term service consumers: the role of action inertia. *Journal of Service Theory and Practice*, 27(1), 270-291. <https://doi.org/10.1108/JSTP-06-2015-0127>
- Lin, J. C., & Chang, H. (2011). The role of technology readiness in self-service technology acceptance. *Managing Service Quality: An International Journal*, 21(4), 424-444. <https://doi.org/10.1108/09604521111146289>
- McDonald, R. P., & Ho, M. H. (2002). Principles and practice in reporting structural equation analyses. *Psychology Methods*, 7(1), 64-82.

- Moudud-UI-Huq, S., Sultana Swarna, R., & Sultana, M. (2021). Elderly and middle-aged intention to use m-health services: an empirical evidence from a developing country. *Journal of Enabling Technologies*, 15(1), 23-39. <https://doi.org/10.1108/JET-04-2020-0018>
- Neslin, S. A., & Shankar, V. (2009). Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions. *Journal of Interactive Marketing*, 23(1), 70-81. <https://doi.org/10.1016/j.intmar.2008.10.005>
- Nysveen, H., Pedersen, P. E., & Thorbjørnsen, H. (2005). Intentions to use mobile services: antecedents and cross-service comparisons. *Journal of the Academy of Marketing Science*, 33(3), 330-346.
- Pan, S., & Jordan-Marsh, M. (2010). Internet use intention and adoption among Chinese older adults: from the expanded technology acceptance model perspective. *Computers in Human Behavior*, 26(5), 1111-1119.
- Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry*, 43(3), 37-40.
- Robinson, L., Jr., Marshall, G. W., & Stamps, M. B. (2005). Sales force use of technology: antecedents to technology acceptance. *Journal of Business Research*, 58(12), 1623-1631. <https://doi.org/10.1016/j.jbusres.2004.07.010>
- Soper, D. S. (2022, May 24). *A-priori Sample Size Calculator for Structural Equation Models*. Danielsoper. www.danielsoper.com/statcalc/default.aspx
- Stibe, A. (2015). Advancing Typology of Computer-Supported Influence: Moderation Effects in Socially Influencing Systems. In T. MacTavish & S. Basapur (Eds.), *Persuasive Technology* (pp. 251-262). Springer.
- Sun, Y., Wang, N., Guo, X., & Peng, Z. (2013). Understanding the acceptance of mobile health services: a comparison and integration of alternative models. *Journal of Electronic Commerce Research*, 14(2), 183.
- Taylor, S., & Todd, P. (1995). Assessing IT usage: the role of prior experience. *MIS Quarterly*, 19(4), 561-570. <https://doi.org/10.2307/249633>
- To, W. M., & Tang, M. N. F. (2019). Computer-based course evaluation: An extended technology acceptance model. *Educational Studies*, 45(2), 131-144.
- Tran, V. D. (2020). Assessing the Effects of Service Quality, Experience Value, Relationship Quality on Behavioral Intentions. *Journal of Asian Finance, Economics and Business*, 7(3), 167-175. <https://doi.org/10.13106/jafeb.2020.vol7.no3.167>
- Venes, D. (2001). *Taber's cyclopedic medical dictionary* (19th ed.). F.A. Davis Company.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27(3), 425-478.
- Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178, <https://doi.org/10.2307/41410412>
- Yuan, D., Rahman, M. K., Issa Gazi, M. A., Rahaman, M. A., Hossain, M. M., & Akter, S. (2021). Analyzing of User Attitudes Toward Intention to Use Social Media for Learning. *SAGE Open*, 11(4), 1-13. <https://doi.org/10.1177/21582440211060784>
- Zeithaml, V. A., Bitner, M. J., & Gremler, D. D. (2006). *Service Marketing* (4th ed.). McGraw-Hill.
- Zhong, K., Feng, D., Yang, M., & Jaruwanakul, T. (2022). Determinants of Attitude, Satisfaction and Behavioral Intention of Online Learning Usage Among Students During COVID-19. *AU-GSB E-JOURNAL*, 15(2), 49-57. <https://doi.org/10.14456/augsbejr.2022.71>