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An Examination of the Components that Increase Acceptance of Smartphones among Healthcare Professionals

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Abstract

Objective: The professional benefits of mobile computing and communication devices such as the smartphone promise to alter the delivery of healthcare services. Historically the healthcare industry has trailed other business sectors in the adoption of technology. Yet, it appears that smartphones are increasingly being embraced by healthcare professionals such as physicians and nurses. Thus, the objective of this study was to investigate the potential factors that may affect the adoption of a smartphone by healthcare professionals. Methods: It is unclear which factors affect the acceptance of mobile computing devices by healthcare professionals. This study integrates the factors from the Technology Acceptance Model, Self-Efficacy, and the Innovation Diffusion Theory to help explain the components which increase smartphone acceptance among healthcare professionals in two countries. We collected 153 surveys from two countries: 88 from the United States and 65 from Taiwan. Results: The results showed that attitude toward using a smartphone and smartphone self-efficacy had a direct positive influence on the intention to use a smartphone. This study also demonstrated that perceived usefulness and task relatedness indirectly influenced the intention to use a smartphone. Discussion: Healthcare professionals who feel they can successfully master the functions of a smartphone are more apt to use the technology. The findings of this study appear to substantiate that healthcare professionals will increasingly embrace smartphones when they perceive them as a useful accompanying tool to further assist with the completion of clinical tasks. Conclusion: As the use of smartphones continues to proliferate, our study should further help researchers more fully understand salient factors which encourage adoption of mobile technologies. Thus, future smartphone applications and software programs can target specific needs of health professionals.

Key Words: Smartphones, TAM, IDT, self-efficacy, health information technology, healthcare professionals, mobile technology

1. Introduction

The recent advances regarding cellular phone technology have enabled mobile devices to perform functions pre-

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viously not possible with handheld devices. These advanced functions have been captured by a new mobile device known as a smartphone. This powerful device is intended to satisfy users by providing operating systems similar to computers in a clinician's hand. Smartphones possess operating systems such as Symbian, Windows Mobile, and Android. These operating systems allow smartphone users to read and edit Microsoft Word, Excel, and PowerPoint files. Additionally, smartphones have enabled users to conveniently access the Internet through wireless connections thereby providing greater data transfer capability. Smartphones also provide high resolution digital cameras, voice and video recording features. These capabilities enable a smartphone to serve as both a mobile computing and communication device and thus become a powerful tool to support healthcare decision-making processes.

The impact of such mobile computing devices on the healthcare industry is expected to be enormous. A medical practitioner's tasks are numerous and include among other responsibilities remaining abreast of contemporary pertinent updates regarding pharmaceuticals, best practice of care options, and completing continuing medical education seminars. Mobile communication devices such as a smartphone have an opportunity to play a vital role in assisting with these responsibilities as well as other tasks. For example, some physicians who are accustomed to writing prescriptions on script pads can use smartphones to transcribe their handwritings into mobile devices for electronic prescribing. Clinicians who traditionally used pagers for on-call activities instead can use smartphones to become acquainted with patient data while en route to the bedside or the hospital. Moreover, the anticipated incorporation of additional medical applications in the near future presumably will only enhance the functionality and use of a smartphone for healthcare professionals.

Although mobile devices have many potential benefits within the healthcare industry, this sector traditionally has been reluctant to embrace current technologies, especially relative to other industries [1, 2, 3]. Yet, it appears that a smartphone are increasingly being embraced by healthcare professionals [4, 5]. This interesting paradox merits further examination.

It is unclear what factors affect the acceptance of mobile computing devices such as a smartphone by healthcare professionals. Thus, our study investigated the potential factors that may affect adoption of smartphones by healthcare professionals. In order to further examine this phenomenon we integrated the factors from three closely related theoretical paradigms-the Technology Acceptance Model (TAM), Self-Efficacy, and the Innovation Diffusion Theory (IDT). Many of these factors have been identified in previous studies of technology adoption and innovation diffusion. Some of the factors were modified after preliminary evaluations were conducted with sample participants.

1.1. Theoretical Backgrounds and Research Hypotheses

Various frameworks and models have been developed to investigate the nature and determinants of information technology (IT) acceptance and adoption. Examples include Fishbein & Ajzen's (1975) Theory of Reasoned Action (TRA), Roger's (1995) Diffusion of Innovations Model, and Davis's (1989) Technology Acceptance Model [6,7,8]. This study integrates components from several models and theories: the TAM, the Self-Efficacy Theory, and the IDT to explain the drivers of smartphone acceptance among healthcare professionals in the United States (US) and Taiwan.

Based on these pre-existing models and theories, we proposed the research model depicted in Figure 1.

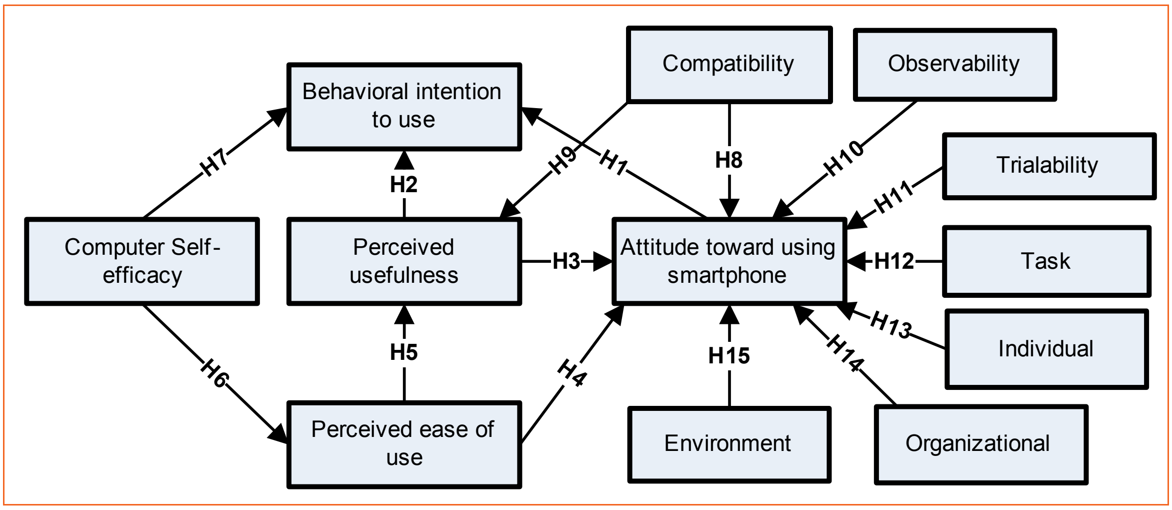

Figure 1: *The Research Model H = hypothesis and the number following each H denotes the corresponding hypothesis number. For example, H1 refers to hypothesis 1.*

1.2. Technology Acceptance Model

Among numerous perspectives that can be used to examine user acceptance and usage behavior of new technologies, TAM might be the most popular one. This model is derived from Fishbein & Ajzen's (1975) Theory of Reasoned Action [6]. Davis (1986) developed TAM specifically for explaining and predicting user acceptance of computer technology [9]. The goal of TAM is "to provide an explanation of the determinants of computer acceptance that is in general, capable of explaining user behavior across a broad range of end-user computing technologies and user populations, while at the same time being both parsimonious and theoretically justified" [page 985] [10].

The Technology Acceptance Model posits the determinants of user acceptance that may be able to explain a user's behavior in regard to a general user's computing technologies. The TAM claims that users evaluate the system based on the system's ease of use (PEOU) and perceived usefulness (PU). If the system is easy to use and useful, a user would have a positive attitude toward the system (AT), which in turn causes a user's actual intention to use (BI). Then, the intention creates a user's decision to use the system.

The TAM's reliability and measurement validity have been demonstrated in various research models operationalized by different criteria such as user types, technology types, and organizational types. TAM has been applied to explain IT acceptance by students [e.g., 10, 11, 12, 13] and non-students [8, 14, 15]. As reported by Ma & Liu (2005), related to the technological context, TAM has been applied to a wide range of technologies, including e-mail, fax, word processors, spreadsheets, and workgroup applications [16]. According to Ma & Liu (2004), there have been over 100 studies applying or validating TAM [17]. In general, results from previous studies suggest that TAM is capable of providing a fairly adequate explanation and prediction of user acceptance of IT [18].

In the context of IT acceptance within the healthcare industry, Hu et al., (1999) examined the applicability of TAM in explaining physicians' decisions to accept telemedicine technology [18]. Chau & Hu (2001) also examined physicians' acceptance of telemedicine technology by evaluating the extent to which dominant intention-related models, including TAM, the Theory of Planned Behavior (TPB), and an integrated model could explain an individual physician's technology acceptance decision [19]. TAM was favored over TPB when examining technology acceptance by professionals because the integrated model may not provide significant additional explanatory power. Using TAM as a foundation, Ma & Liu (2005) investigated the acceptance of web-based electronic medical records (EMRs) among senior health care trainees [16]. Their results showed that PU and PEOU have a significant positive effect on the intention to use EMRs.

Our study proposed the following hypotheses based on the TAM framework.

Hypothesis 1: The attitude toward using a smartphone has a significant positive effect on the behavioral intention to use a smartphone.

Hypothesis 2: The perceived usefulness of a smartphone has a significant positive effect on the behavioral intention to use a smartphone.

Hypothesis 3: The perceived usefulness of a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 4: The perceived ease of use of a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 5: The perceived ease of use of a smartphone has a significant positive effect on the perceived usefulness of a smartphone.

1.3. Smartphone Self-Efficacy

Compared with competing models, TAM is believed to be more accurate and parsimonious when it is used to predict technology adoption [16]. However, the parsimony of TAM often results in the model being less informative in understanding usage behavior [12]. Due to this limitation, researchers have attempted to extend the TAM framework by encompassing various constructs such as gender, culture, trust, experience, social influence, and self-efficacy [20, 21, 22]. Among those constructs, self-efficacy is recognized to be a more important than the others [16].

Efficacy refers to the belief that an individual has the ability to perform a particular behavior [23]. Self-efficacy has been documented in numerous studies to be an important determinant of PEOU [24, 25, 26]. In the context of Web technologies, Agrawal et al (2000) found a positive effect of self-efficacy on both PU and PEOU [24]. Similarly, Ma & Liu (2005) found that self-efficacy positively influences PU, PEOU, and the intention to use web-based EMRs [16].

In this study, we define smartphone self-efficacy as an individual's belief regarding his/her ability to use a smartphone. Based on the above discussion, we propose the following hypotheses.

Hypothesis 6: Self-efficacy to a smartphone has a significant positive effect on the perceived ease of use of a smartphone.

Hypothesis 7: Self-efficacy to a smartphone has a significant positive effect on the behavioral intention to use a smartphone.

1.4. Innovation Diffusion Theory

The IDT posits an array of innovation characteristics that may impact a user's perception of the innovation preceding adoption of the innovation. As a result, these characteristics presumably affect the speed of innovations being embraced. These attributes further provide a theoretically-based set of socio-behavioral beliefs. Thus, we adopted IDT because of the innovative nature of smartphone devices. Innovation may be defined as a new use of an idea, practice, or object by the unit of adoption [27]. This definition of innovation can be applied to new technology adoptions among individuals and within healthcare IT [7].

Previous innovation diffusion studies have suggested that innovation attributes affect an individual's attitude of the innovation prior to adoption and may consequently influence the speed of adoptions [28]. This study employed these attributes in building the theoretical basis for behavioral characteristics. These beliefs include relative advantage, compatibility, complexity, trialability, and observability [29]. Relative advantage refers to the degree to which adopting/using IT innovation is perceived as being better than using the practice it supersedes [30]. Compatibility refers to the degree to which adopting the IT innovation is consistent with the existing values, needs, and past experiences of potential adopters [28]. Complexity refers to the relative difficulty in operation of the new IT innovation. Trialability refers to the degree to which one can experiment with an innovation on a limited basis before making an adoption or rejection decision [28]. Observability refers to the degree to which the results of adopting/using the IT innovation are observable and communicable to others [28].

Kwon & Zmud (1987) suggest that when discussing IDT-related subjects' factors such as task, individual, organization, and environment as additional explanatory factors should be introduced [30]. Task includes structure of the task, jurisdiction, and uncertainty. Individual factors include aspects such as education, age, experience, and personal specialties. Organizational factors include the support of higher-level management, the organizational structure, the involvedness of the users, and the quality of the product. Environmental factors include pressure from competitors, customer satisfaction, and marketing strategies. The context of smartphone adoption contains both individual factors and organizational diffusion. Based on the above discussion regarding IDT factors, the following relationships were hypothesized.

Hypothesis 8: The compatibility with a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 9: The compatibility with a smartphone has a significant positive effect on the perceived usefulness of a smartphone.

Hypothesis 10: The observability of a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 11: The trialability of a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 12: The task relatedness with a smartphone has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 13: The individual feature has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 14: The surrounding organization has a significant positive effect on the attitude toward using a smartphone.

Hypothesis 15: The environment has a significant positive effect on the attitude toward using a smartphone.

2. Methods

2.1. Sample

The sample of this study consisted of healthcare professionals (i.e., physicians and nurses) who either had previously used or were currently using a smartphone in practice. Our sample was conveniently selected from one hospital in the Midwestern US and one hospital in Taiwan. In the original data set, a total of 200 surveys were collected, consisting of 73 respondents from Taiwan and 127 respondents from the US. The data sets were then examined for missing or incomplete questionnaires, resulting in a total of 153 completed questionnaires (i.e., 88 from the US and 65 from Taiwan).

2.2. Instrument Development

Two sets of questionnaires were developed. One set of the questionnaire was written in English and was used in the US sample. The questionnaire was approved by the university and hospital institutional review boards. The other survey was written in Chinese and used among Taiwan healthcare professionals. The instruments were reviewed by an independent researcher to ensure that the items' meaning was consistent in English and Chinese.

The survey instrument consisted of three sections. The first section contained definitions of pertinent terms and instructions to complete the questionnaire. The second section contained items used to measure the independent variables assumed to affect smartphone adoption. A five-point Likert scale from strongly disagree to strongly agree was used to measure the items. Many of the items were borrowed from previous studies. The third section contained questions about respondent demographics. Statistical software packages, SPSS and AMOS, were used for data analysis. Table 1 shows the variables and items along with the matching sources.

Variable	Number of Items	Source(s)
Self-Efficacy	10	23
Perceived Usefulness	6	8
Perceived Ease of Use	6	8
Behavioral Intention to Use	4	14 and 26
Attitude toward using	4	10
Trialability	4	31
Observability	2	31 and 32
Comparability	3	31 and 32
Task	3	31 and 32
Individual	4	31 and 32
Organization	5	31 and 32
Environment	2	31 and 32

Table 1: *Summary of Research Variables.*

2.3. Measurement Model

Reliability and convergent validity assessment were performed after collection of the surveys by examining item-to-total correlation, Cronbach's alpha coefficients, and employing factor analysis. Consequent to these assessments, several items were omitted from further analysis [33].

Cronbach's alpha coefficients were computed to estimate the reliability of each construct. In refining the measures and eliminating lower alpha coefficients, we used item-to-total correlation. Items with item-to-total correlation coefficient less than 0.50 were eliminated [34]. Based on the criteria above, four items were deleted (AT2, TI4, TASK3, and ENV2). The Cronbach's alpha of the final measures ranged from 0.619 to 0.956, which is considered within the acceptable range. The reliability coefficient (Cronbach's alpha) of the constructs is presented in Table 2.

Variable	Number of Original Items	Number of Retained Items	Cronbach's Alpha
Self-Efficacy	10	10	.831
Perceived Usefulness	6	6	.956
Perceived Ease of Use	6	6	.938
Behavioral Intention to Use	4	4	.927
Attitude toward using	4	3	.917

Table 2: *Reliability Coefficients of the Constructs.*

Trialability	4	3	.873
Observability	2	2	.789
Comparability	3	3	.913
Task	3	2	.768
Individual	4	4	.747
Organization	5	5	.619
Environment	2	1	NA

Table 2: *Reliability Coefficients of the Constructs.*

After meeting the minimum levels of reliability, they were assessed for convergent validity. A principal component of factor analysis with varimax rotation (SPSS orthogonal rotation) was performed to test the unidimensionality of each scale, which retained items or manifest indicators. Items with factor loading <0.5 in the corresponding factor were eliminated from further consideration [34]. Results indicated that SE1, SE2, SE3, and SE4 did not load cleanly on the factor representing the expected construct. Thus, these four items were eliminated from further consideration.

2.4. Summed-Scale Indicator

We combined the items measuring each construct into a single indicator measure principally because the final sample was relatively small compared to the parameters to be estimated [35]. Factor score weights obtained from confirmatory factor analysis (CFA) of each construct was used to create composite measures (indicators) of the corresponding latent constructs (save the constructs with only two items). This was performed by using an AMOS software package.

There were several reasons for using composite scores as an indicators rather than individual items as indicators of the latent variables. First, there were software computing limitations and difficulties fitting models with too many manifest indicators. Second, composite scores enabled the researchers to represent several variables by a single indicator that reduced the difficulties of moderate sample sizes. The utilization of composite scores reduced the number of parameters to be estimated and yielded an acceptable variable-to-sample size ratio [34, 36].

When using a single composite indicator for a latent construct, the indicator is not likely to perfectly estimate the construct. As recommended by Howell (1987), the measurement error terms was fixed at $(1-\alpha)\ \sigma 2$ and the corresponding lambdas – the loading from a latent construct to its corresponding indicator – was fixed at $\alpha 1/2\sigma$ [37]. The constructs with only two items (OB and TASK) continue using individual items as indicators, while regarding the construct with a single item (ENV), the error term was fixed at 0 and the corresponding lambda was fixed at 1.

The composite reliability (α) measures the internal consistency of the construct indicators, depicting the degree to which they indicate the common latent (unobserved) construct. The computation of α is as follows:

$$\alpha = \frac{(\text{sum of standardized loadings})^2}{(\text{sum of standardized loadings})^2 + (\text{sum of indicator measurement errors})}$$

Whereas indicator measurement errors are calculated as: $\varepsilon j = 1 - (\text{standardized loading})^2$

Based on the calculation above, the construct reliability, lambda, and error term of the constructs are shown in Table 3.

Variable	alpha	lambda	E
Self-Efficacy	.830	.540	.060
Perceived Usefulness	.956	.791	.029
Perceived Ease of Use	.938	.739	.036
Behavioral Intention to Use	.929	.722	.040

Table 3: *Reliability Coefficients of the Constructs.*

Attitude toward using	.918	.720	.046
Trialability	.884	.618	.050
Observability	-	-	-
Comparability	.915	.810	.060
Task	-	-	-
Individual	.760	.584	.108
Organization	.625	.360	.078
Environment	-	1	0

Table 3: *Reliability Coefficients of the Constructs.*

3. Results

3.1. The Structural Model

Six indicators were used to test the goodness-of-fit of the model and the results are displayed in Table 4.

Fit Index	Recommended Value	Result
Chi-square	$p \geq .050$	.000
Chi-square/df	$\leq$ 3.00	2.533
GFI	$\geq$ .900	.918
AGFI	$\geq$ .800	.809
CFI	$\geq$ .900	.929
RMSEA	$\leq$ .080	.100

Table 4: *Goodness-of-fit Statistics.*

The structural model produces the following path coefficient as shown in Table 5.

Hypothesis	Path	Standardized Regression Weight	*p*
H1	BI ← AT	.536	.000
H2	BI ← PU	.242	.095
H3	AT ← PU	.629	.000
H4	AT ← PEOU	.089	.132

Table 5: *Structural Model Statistics; BI = Behavioral intention to use; AT = Attitude toward using; PU = Perceived usefulness; PEOU = Perceived ease of use; SE = self-efficacy; CM = Compatability; OB = Observability; TI = Trialability; TASK = Task; IND = Individual; ORG = Organization; ENV = Environment.*

H5	PU ← PEOU	.026	.673
H6	PEOU ← SE	.301	.000
H7	BI ← SE	.219	.000
H8	AT ← CM	.131	.359
H9	PU ← CM	.871	.000
H10	AT ← OB	.002	.967
H11	AT ← TI	.012	.830
H12	AT ← TASK	.188	.048
H13	AT ← IND	.037	.533
H14	AT ← ORG	.046	.596
H15	AT ← ENV	-.020	.758

Table 5: *Structural Model Statistics; BI = Behavioral intention to use; AT = Attitude toward using; PU = Perceived usefulness; PEOU = Perceived ease of use; SE = self-efficacy; CM = Compatability; OB = Observability; TI = Trialability; TASK = Task; IND = Individual; ORG = Organization; ENV = Environment.*

Some of the goodness-of-fit criteria were not met, thus further investigation was conducted to find the possible causes. From the modification indices (MI), we found that adding a path from compatibility to PEOU significantly improved the model (MI = 44.982). Based on theoretical justification, we added the path and the results are presented in Table 6 and Table 7.

Fit Index	Recommended Value	Result
Chi-square	$p \geq .050$	.189
Chi-square/df	≤ 3.00	1.183
GFI	$\geq .900$	.956
AGFI	$\geq .800$	.896
CFI	$\geq .900$	.992
RMR	$\leq .050$	.022
RMSEA	$\leq .080$	.035

Table 6: *Goodness-of-fit Statistics of Modified Model.*

Hypothesis	Path	Standardized Regression Weight	*p*
H1	BI ← AT	.555	.000
H2	BI ← PU	.242	.094
H3	AT ← PU	.610	.000
H4	AT ← PEOU	.076	.227
H5	PU ← PEOU	-.047	.501
H6	PEOU ← SE	.093	.217
H7	BI ← SE	.211	.000
H8	AT ← CM	.130	.377
H9	PU ← CM	.908	.000
H10	AT ← OB	.002	.970
H11	AT ← TI	.011	.829
H12	AT ← TASK	.181	.046
H13	AT ← IND	.036	.518
H14	AT ← ORG	.046	.587
H15	AT ← ENV	-.020	.751
Additional path	PEOU ← CM	.631	.000

Table 7: *Structural Model Statistics of Modified Model BI = Behavioral intention to use; AT = Attitude toward using; PU = Perceived usefulness; PEOU = Perceived ease of use; SE = self-efficacy; CM = Compatability; OB = Observability; TI = Trialability; TASK = Task; IND = Individual; ORG = Organization; ENV = Environment.*

There are many hypotheses postulated in this study. Thus, Table 8 displays a summary of the significant hypotheses in our study.

Hypothesis	Path	*p*
H1	BI ← AT	.000
H3	AT ← PU	.000
H7	BI ← SE	.000
H9	PU ← CM	.000
H12	AT ← TASK	.046

Table 8: *Summary of Regression Model; BI = Behavioral intention to use; AT = Attitude toward using; PU = Perceived usefulness; PEOU = Perceived ease of use; SE = self-efficacy; CM = Compatibility; TASK = Task.*

Additional path	PEOU ← CM	.000

***Table 8:** Summary of Regression Model; BI = Behavioral intention to use; AT = Attitude toward using; PU = Perceived usefulness; PEOU = Perceived ease of use; SE = self-efficacy; CM = Compatibility; TASK = Task.*

4. Discussion

The results of this study showed that five of the 15 hypotheses were supported (displayed in Table 8). The attitude toward a smartphone was shown to positively influence the intention to use a smartphone (β=.555, $p \geq .000$). This finding provided support for hypothesis one. Perceived usefulness had a significant positive effect on the attitude toward using a smartphone (β=.610, $p \leq .000$), thus supporting hypothesis three. The results also provided support to hypothesis seven, which showed that smartphone self-efficacy influenced a user's intention to use a smartphone (β=.211, $p \leq .000$). A user's compatibility with a smartphone was found to significantly affect the perceived usefulness of a smartphone (β=.908, $p \leq .000$), thus providing support to hypothesis nine. The results also supported hypothesis 12 that task relatedness with a smartphone positively influenced a user's attitude toward using a smartphone (β=.181, $p \leq .046$). Our study further found that compatibility had a positive effect on the PEOU.

The results indicated that attitude toward using a smartphone tends to determine behavioral intention to use a smartphone. Perceived usefulness positively determined attitude toward using smartphone, but not the PEOU. This result is relatively consistent with previous studies [25]. This may imply that a healthcare professional's overall feeling about a smartphone's usefulness may be a more influential factor than a medical practitioner's perception of the ease of use of a smartphone in determining a healthcare professional's attitude toward using such a device. Some older studies such as Davis et al. (1989) did not give much importance to the attitude construct in explaining the user acceptance [10]. This finding may warrant further investigation.

The findings also suggested that smartphone self-efficacy tends to determine intention to use a smartphone. However, in our modified and final model this was not shown that smartphone self-efficacy tends to determine PEOU. Nevertheless, a previous study has shown that self-efficacy positively affected healthcare professionals' PEOU of web-based EMRs [16]. A possible implication from our study is that if healthcare professionals think positively about their mobile computing skills they generally demonstrate a higher level of intention to use a smartphone in their clinical activities. The application of factors from TAM into healthcare professionals' intention of mobile technology use and particularly smartphone use is relatively novel. It is relevant because smartphones are increasingly being embraced by healthcare professionals [4, 5]. Our study shows that by applying a TAM model, the intention to use a smartphone presumably can be explained by healthcare a professional's attitude toward a smartphone.

Our research model also includes Rogers' innovation factors (namely, observability, compatibility, trialability, task, individual features, organizational characteristics, and environmental factors) and these factors were tested to determine if these components affected attitudes toward using smartphones. In our study, only the task characteristic among the innovation attributes was positively related with healthcare professionals' attitude toward using a smartphone. It should be noted that compatibility also showed a significant positive impact on both perceived usefulness and perceived ease of use. This evidence indicates that if the use of a smartphone is compatible with a medical practitioner's existing values, needs, and past experience, he/she will eventually perceive a smartphone to be useful and easy to use and presumably may adopt a smartphone to assist with clinical duties.

Our study had a few limitations. The perceptions of smartphone adoption in this study were based on a one time survey. A longitudinal study which more thoroughly measures a healthcare professional's attitude longitudinally would presumably promote greater reliability. Another limitation was the lack of an environmental context. It should also be noted that our samples were based on a single hospital in each country. A future study that examines research relationships across multiple hospitals in each country presumably would improve generalization of smartphone adoption among healthcare professionals.

5. Conclusion

Our domain of research, the smartphone, is a relatively new technology. Our study of smartphone adoption by healthcare professionals discusses factors that promote smartphone use and why smartphones may be increasingly embraced by health practitioners. The study results supported the premise that the attitude of a professional regarding a smartphone tends to signify a positive intention to use such a mobile device. This study presents a novel attempt to investigate smartphone adoption by applying new settings to emerging technologies. Consequently, it should assist health researchers broaden the range of research contexts. Prior research has concluded that attitude and behavioral intention exist in both TAM and IDT; thus, various characteristics related to attitude and behavioral intentions were synthesized in a smartphone adoption model among professionals. Therefore, our study extended prior research by providing the synthesized constructs for the domain of healthcare professionals in the US and Taiwan.

An important implication of this study is the strategic planning value in examining the factors which affect acceptance of emerging mobile technologies by healthcare professionals. Health administrators spend vast sums of capital on novel and untested technologies to improve the delivery of healthcare services. However, many of these information systems and software programs are not readily embraced by the practitioners. Thus, studies that examine which factors are beneficial or detrimental toward adopting and accepting emerging technologies may prove particularly cost-effective for healthcare organizations and individual practitioners.

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