international journal of medical informatics 76 (2007) 66–77

journal homepage: www.intl.elsevierhealth.com/journals/ijmi

Mobile computing acceptance factors in the healthcare industry: A structural equation model

Jen-Her Wu[a,b,*], *Shu-Ching Wang*[a,c], *Li-Min Lin*[d]

[a] *Department of Information Management, National Sun Yat-sen University, 70 Lien-Hai Road, Kaohsiung 804, Taiwan*
[b] *Institute of Health Care Management, National Sun Yat-sen University, Kaohsiung 804, Taiwan*
[c] *Department of Information Management, National Kaohsiung Marine University, Kaohsiung 811, Taiwan*
[d] *Department of Nursing, Mei-Ho Institute of Technology, Kaohsiung, Pingtung 912, Taiwan*

ARTICLE INFO

Article history:
Received 2 March 2005
Received in revised form
27 March 2006
Accepted 28 June 2006

Keywords:
Health care
Mobile healthcare
Technology acceptance
Compatibility
Self-efficacy
Technical support and training

ABSTRACT

Objective: This paper presents a revised technology acceptance model to examine what determines mobile healthcare systems (MHS) acceptance by healthcare professionals.
Method: Conformation factor analysis was performed to test the reliability and validity of the measurement model. The structural equation modeling technique was used to evaluate the causal model.
Results: The results indicated that compatibility, perceived usefulness and perceived ease of use significantly affected healthcare professional behavioral intent. MHS self-efficacy had strong indirect impact on healthcare professional behavioral intent through the mediators of perceived usefulness and perceived ease of use. Yet, the hypotheses for technical support and training effects on the perceived usefulness and perceived ease of use were not supported.
Conclusion: This paper provides initial insights into factors that are likely to be significant antecedents of planning and implementing mobile healthcare to enhance professionals' MHS acceptance. The proposed model variables explained 70% of the variance in behavioral intention to use MHS; further study is needed to explore extra significant antecedents of new IT/IS acceptance for mobile healthcare. Such as privacy and security issue, system and information quality, limitations of mobile devices; the above may be other interesting factors for implementing mobile healthcare and could be conducted by qualitative research.

1. Introduction

The healthcare industry, conventionally, is recognized as having lagged behind other industries in the use and adoption of new information technologies (IT) and information systems (IS) [1–4]. However, this situation is shifting at a fast pace. Modern IT/IS is an essential tool that fosters and promotes progress in health care and drastically reforms current health care practices. Mobile IT/IS applications in health care can be recognized as both emerging and enabling technologies [5–7] that have been applied in several countries for emergency care or general health care. For example, a variety of wireless technologies such as mobile computing, wireless networks and global positioning systems (GPS) have been applied to ambulance care in Sweden [8] and emergency trauma care in the Netherlands [9]. Relevant information about the patient

* *Corresponding author at*: Department of Information Management, National Sun Yat-sen University, 70 Lien-Hai Road, Kaohsiung 804, Taiwan. Tel.: +886 7 5254722.
E-mail address: jhwu@mis.nsysu.edu.tw (J.-H. Wu).
1386-5056/$ – see front matter
doi:10.1016/j.ijmedinf.2006.06.006

(vital information) and the ambulance (exact time and location) can be transmitted to the hospital in real-time. Therefore, the hospital can be well-prepared for ambulance arrival. In Finland, a system with secure mobile healthcare services was tested in 2003 and was available nationwide in 2004. This system includes health consulting, electronic prescription, etc. Authorized individuals can easily access the system via mobile devices such as mobile phones [10].

Furthermore, health care professionals also need to access and input medical or patient information from anywhere, at any time in their daily ward rounds [7,11,12]. Hence, mobile healthcare systems can facilitate efficient and effective patient care information input and access at the point of patient care. The systems can improve patient care and quality of services, decrease clinical errors, integrate resources, and enable ubiquitous real-time access to patient information and up-to-date medical knowledge [5,12–15]. However, most applications, in fact, have failed [16] or have not been implemented as predicted [17]. Among these, 30% of the failure rate results from non-technical factors [18,19]. Insufficient user acceptance has long been an obstacle to the successful adoption of IT/IS. Therefore, it is extremely significant to probe the determinants crucial to advance IT/IS acceptance by healthcare professionals.

With accelerated hospital competition and the popularity of the Internet and mobile devices, there is a need to understand the factors that would entice healthcare professionals to use mobile healthcare systems (MHS). Comprehending the essentials of what determines healthcare professional MHS acceptance can provide great management insight into developing effective strategies that will allow hospitals to create new opportunities and values for its customers, to increase the efficiency and effectiveness of health care personnel, and thereby, remain competitive. Generally, the essential characteristics of users and technologies in professional healthcare differ greatly from the customary commercial context [20]. Thus, any model developed for the general public may not apply to a healthcare environment. MHS acceptance may need to consider MHS-specific factors, such as healthcare professional values and their mobile computing capabilities. Hence, the purpose of this study is to present a conceptual framework for assessing the medical professional behavioral intention to adopt MHS. Technology acceptance model (TAM) and the innovation diffusion theory (IDT) serve as the theoretical basis for this study that are integrated with MHS self-efficacy, and technical support and training. We also validate the factors that determine healthcare professional MHS acceptance and examine the relationships among those latent variables.

2. Conceptual model and research hypotheses

In this study, MHS refers to the healthcare information processing system, including all relevant medical professional participants and the use of new IT/IS to deliver healthcare services and exchange healthcare information via mobile devices anytime and anywhere [1,20–22]. Healthcare professional MHS adoption refers to the healthcare professionals' psychological state regarding the individuals' intention to use MHS in their practice. The integrated mobile IT/IS can provide easy access to the networks and resources whether the healthcare professionals or patients are stationary or moving. MHS allows professionals to access real-time patient records and state-of-the-art medical information [5,14]. The variety of mobile devices includes personal digital assistants (PDAs), laptops, pocket and tablet computers, GPS, smart-phones, etc. [10,22–24]. While system use is recognized as a good indicator of IT/IS success, user adoption and system acceptance can be predicted adequately from the individual's behavioral intent. A number of empirical studies have proven this point [20,21,25,26].

Based on our observation and intensive literature review, there are several important factors for determining the success of modern IT/IS in health care; for example, the reluctance of healthcare professionals to use systems as a consequence of limitations in their IT skills [17,27]. Other potential determinants may found in the answers to the following questions: how IT/IS is compatible with healthcare practitioners' current working conditions; what kinds of training programs, resources and support were provided; what incentives were used to get healthcare professionals to use the system [5]. In addition, some studies indicated that mobile device size, access procedures, ease of use, mobile interface, and training and support are the most significant factors for new application usage [23,28]. These issues are described as follows.

2.1. *Technology acceptance model and innovation diffusion theory*

The users' acceptance of new IT/IS is the primary factor in IT/IS success [21]. Technology acceptance model is a well-established model that has been used broadly to predict and explain human behavior [29,30]. The initial TAM is composed of five constructs: perceived ease of use (PEOU), perceived usefulness (PU), attitude toward using (ATU), behavioral intention to use (BI), and actual system use (AU). Among these, PU and PEOU are the most dominant determinants for system use and PEOU has a direct effect on PU. Attitude toward using directly influences a user's behavioral intention to use determining actual system use. Venkatesh and Davis [31] proposed an extended TAM, labeled TAM2 which omits attitude toward using because of weak predictors of either behavioral intention to use or actual system use. In other words, behavioral intention to use is jointly determined by PU and PEOU. This means that healthcare professional perceptions of the degree to which MHS is easy to use influences both perception of usefulness and the professional intentions to use MHS. The professionals' intentions to use MHS can be explained or predicted by the perception of MHS ease of use and usefulness [30,32]. Therefore, the following hypotheses are proposed.

H1. Perceived usefulness has a direct effect on behavioral intention to use MHS.

H2a. Perceived ease of use has a direct effect on behavioral intention to use MHS.

H2b. Perceived ease of use has a direct effect on perceived usefulness.

Although a previous study indicated that TAM presents a good explanation for examining physicians' acceptance of telemedicine technology [20], many studies [31,33] suggested that TAM needed to be extended and incorporated with further constructs to enhance its explanation and prediction of acceptance behavior. Innovation diffusion theory is another well-known theory proposed by Rogers [34,35] and has been widely applied in relevant IT/IS studies. IDT includes five significant innovation characteristics: relative advantage, compatibility, complexity, trialability, and observability. Yet, only the relative advantage, compatibility, and complexity were consistently related to innovation adoption [33].

Compatibility is one of the important innovation characteristics and refers to the degree to which the innovation is perceived to be consistent with potential users' existing values, prior experiences and needs [33–35]. High compatibility can result in preferable adoption. Prior studies indicated that compatibility had strong direct impact on the variation in behavioral intention and explained more of it in using group support system [36] and in adopting new methodology for software development [37] as well as university smart card [38]. These findings are consistent with other numerous empirical evidences that the better MHS is matched with clinical and patient care working practices, the higher MHS acceptance will be achieved [3,10,11,18,24,25,27].

TAM and IDT are extremely similar in some constructs and also supplement each other. While relative advantage is similar to perceived usefulness, complexity is similar to perceived ease of use. Hence, some researchers indicated that the constructs employed in TAM are fundamentally a subset of the perceived innovation characteristics [33] and, if integrated, could provide an even stronger model than standing alone. Thus, Horan et al. [25] integrated the work practice compatibility and TAM to examine physician acceptance of an online disability evaluation system. The results evidenced that work practice compatibility is an important factor in predicting behavioral intent. In addition, the authors suggested that physicians are more likely to use new IT/IS already in current practice. Likewise, compatibility, TAM and theory of planned behavior were integrated together to test physicians' acceptance of telemedicine technology by Chau and Hu [39]. The study asserted that the physicians would be more likely to take IT/IS usefulness into account if they regarded it as being compatible with their current healthcare practices. Physicians would also prefer an easy-to-use IT/IS without radical changes in their work behavior [7,11,18]. Hence, the following hypotheses are proposed.

H3a. Compatibility has a direct effect on behavioral intention to use MHS.

H3b. Compatibility has a direct effect on perceived usefulness.

H3c. Compatibility has a direct effect on perceived ease of use.

2.2. *Mobile healthcare systems self-efficacy*

Self-efficacy was defined by Bandura as "people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills one has but with judgments of what one can do with whatever skills one possesses" [40]. This belief has an influence on one's ability to perform a specific task, degree of effort expended, and persistence of effort. Self-efficacy measures should be tailored to the targeted domain context [40–42], such as computer self-efficacy and Internet self-efficacy.

In the context of mobile healthcare, the characteristics and operations of mobile devices (e.g., PDAs, tablet PCs, smartphones, etc.) may differ from those used for traditional computing or communication devices (such as desk computers). As a consequence, MHS self-efficacy is more preferable than computer self-efficacy or Internet self-efficacy for mobile healthcare. While the mobile IT/IS is more compatible with health care professionals' existing values, previous experiences and practice needs, they will feel more comfortable and confident in using MHS and this will result in higher perceptions of MHS self-efficacy. Therefore, the following hypothesis is proposed.

H3d. Compatibility has a direct effect on MHS self-efficacy of using MHS.

A number of studies have evidenced that computer self-efficacy is a significant construct in determining individual's behavior toward future use of computers [43–47], especially in the early adoption stage. Currently, the mobile healthcare settings are still in its infancy. As previous studies stated, it will be a challenge for healthcare professionals to employ a new mobile IT/IS system such as MHS due to their low computer literacy [20,21,27]. The healthcare professionals with little confidence in their capability to adopt mobile computing may cause poor performance on mobile healthcare as well as result in diminishing their intentions to use MHS. Therefore, computer self-efficacy has been widely applied in IT/IS studies and is considerably positive contributing to individuals' perceptions of system ease of use and usefulness [45–49]. Based on the preceding discussion, the following hypotheses are proposed.

H4a. MHS self-efficacy has a direct effect on perceived usefulness of using MHS.

H4b. MHS self-efficacy has a direct effect on perceived ease of use on MHS.

2.3. *Technical support and training*

Technical support and training (TST) is another crucial factor in new IT/IS acceptance because theory and evidence assert that individual perceptions in new IT/IS acceptance may increase over time with sufficient support [19,44,45,50]. To facilitate the efficient and effective mobile healthcare, it is essential to have a better understanding about what practitioners need and to improve their technical skills with

Table 1 – Definition of the constructs

Construct	Definition	Reference
Compatibility	The degree to which the use of MHS is perceived to be consistent with health-care professionals' existing values, prior experiences and needs	[34,35]
MHS self-efficacy	The healthcare professional's perceptions of his or her ability to use MHS in the accomplishment of healthcare task	[45,52]
Technical support and training	The technical support and the amount of training provided by individuals or groups with the MHS knowledge	[50]
Perceived usefulness	The degree to which a healthcare professional believes that the use of MHS would enhance his or her performance	[29,30]
Perceived ease of use	The degree to which a healthcare professional believes that the use of MHS would be free of physical and mental effort	[29,30]
Behavioral Intention to use	The degree to which a healthcare professional's motivation intend to use the MHS	[20,21]

necessary and well-matched resources (including wireless network infrastructures, hardware/software, consultants and all relevant information). Support comprises various perspectives of users' demands such as technical consultants, related training programs, appropriate and sufficient resources from either internal or external organizations [19,50].

Venkatesh [48] also asserted that organizations should consider providing general computer training programs to increase users' computer awareness and self-efficacy. In addition, a number of studies [42–45,51] suggested that given valuable training programs and technical support will efficiently enhance individual capabilities and their perceptions and also increase their perceptions of system ease of use and usefulness [19,50]. This infers that technical support and training has strong correlations with MHS self-efficacy and professionals' perceptions of system ease of use and usefulness at the early stage of MHS implementation. As a result, required resources must be appropriately and sufficiently allocated and the healthcare working processes must be integrated and optimized to fit the new mobile IT/IS adoptions. This effort will make healthcare professionals more comfortable with the MHS context and enhance their confidence in using mobile IT/IS. Therefore, the following hypotheses are proposed.

H5a. Technical support and training has a direct effect on the perceived usefulness of MHS.

H5b. Technical support and training has a direct effect on perceived MHS ease of use.

H5c. Technical support and training has a direct effect on the individual's perception of MHS self-efficacy.

2.4. *Definitions and research model*

Based on the foregoing discussions, this study integrated the technology acceptance model with three additional variables (i.e., technical support and training, compatibility, and MHS self-efficacy) to model healthcare professionals' MHS acceptance in the healthcare environment. Table 1 summarizes the definition of each construct and the conceptual research model is also depicted in Fig. 1.

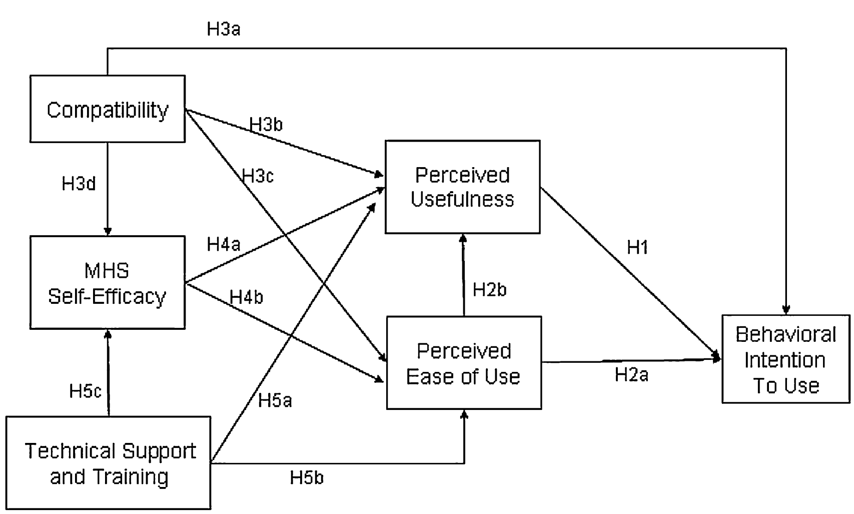

Fig. 1 – Conceptual model for mobile healthcare. *Note:* Pointing arrows show that starting point has a direct impact on the ending point.

3. Research methodology and design

3.1. Model instruments

A number of prior relevant studies were reviewed to ensure that a comprehensive list of measures was included. All measures for each construct were taken from the previously validated instruments and modified based on the mobile healthcare context. Those for perceived usefulness, perceived ease of use, and intention to use were derived from previous studies on TAM [20,29,30,39]. The measures for technical support and training were elicited from Igbaria et al. [50]. The construct for compatibility was obtained from Rogers [34,35] and Chau and Hu [39], whereas the items for MHS self-efficacy were captured using three items tailored from Compeau and Higgins [45] and Venkatesh et al. [52].

The survey questionnaire consisted of three parts. The first part gave a concise instruction and the MHS definition for this study. The second part consisted of six questions capturing the demographic characteristics of the subject, involving what mobile healthcare applications and mobile equipments were actually used by the subject, type of hospitals, ownership of the hospital, subject's position and age. The last part recorded the subject's perception of each variable in the model. This part asked each subject to indicate his or her degree of agreement with each item. Data were collected using a five point Likert-type scale from one, being "strongly disagree", to five, being "strongly agree".

Once the initial questionnaire was generated, an iterative personal interview process with the domain experts from medical institutes and well-known hospitals (including two faculties, three physicians, four nurses and two medical technicians) was conducted to verify the completeness, wording, and appropriateness of the instrument and to confirm the content validity. The review process was conducted to refine the instrument until no further modification to the questionnaire was needed. Several iterations were conducted and feedback served as a basis for correcting, refining and enhancing the experimental measures. Some questions were eliminated because they were found to represent essentially the same aspects as other questions with only slight wording differences. Some questions were modified because the semantics appeared ambiguously or irrelevant to MHS characteristics. The self-administered questionnaire consisted of 18 items measuring the six latent variables.

3.2. Subjects

Subjects for this study were users engaged in mobile healthcare systems, including physicians, nurses, and medical technicians that work for hospitals in Taiwan. The Taiwan Government launched its National Mobile Infrastructure Project in 2002 and claimed that by year 2006 Taiwan would be a mobile island. However, currently, mobile healthcare systems in Taiwan are still in the early implementation stage. Only nine well-known hospitals have actually implemented or partially implemented MHS. Thus, we distributed 291 questionnaires with a souvenir to all targeted hospitals that actually or partially implemented MHS. Data were collected via snowball and convenient sampling. Since the desired sample characteristic was extremely rare and the conventional low survey response rates in health care organizations, we endeavored to find a specific local contact person for each targeted hospital that was placed in charge of distributing the questionnaire and the follow-up activities.

3.3. Analysis methods

The reliability and validity of the measurement model was assessed by a confirmatory factor analysis (CFA) [53–56] using the LISREL software and the maximum likelihood method was applied to estimate the parameters of the model. This step was used to test if the empirical data conformed to the presumed model. Then, the structural equation modeling (SEM) [53–56] technique was used to examine the causal model.

4. Data analysis and results

4.1. Descriptive statistics

One hundred and thirty-seven returned questionnaires were received. Data were excluded to ensure the construct validity while a respondent gave incomplete answers for each construct. Fourteen questionnaires were dropped because 10 gave invalid answers (e.g., never use MHS) and the rest 4 did not meet the criteria of each construct. This left 123 questionnaires for the statistical analysis, a 42.27% valid return rate. Among these, based on the screening criteria, there were nine valid questionnaires with only one missing value within the major six constructs except for demographics information; therefore, mean substitution was used to generate replacement values for the missing data of the construct [56].

Table 2 illustrates the sample demographics. The data shows that the Picture Archiving and Communication Systems (PACS) and the mobile order systems were the most and second frequently adopted MHS. Tablet PCs was the equipment type most often used by clinical professionals and at least two times more often as any other equipment in the mobile healthcare setting. The data also indicated that medical centers have the highest MHS implementation rate, two times more often as all other medical units. In contrast, the public hospitals have the lowest implementation rate. Among the subjects, nurses are the major MHS users. Furthermore, the mean age is 29.6 with standard deviation 6.34 and the respondents' age was from 20 to 49.

4.2. Validity and reliability of the measurement model

The model included 18 items describing six latent constructs: technical support and training, compatibility, MHS self-efficacy, perceived usefulness, perceived ease of use and behavioral intention to use. The various goodness-of-fit statistics are shown in Table 3 and present a good fit between the data and the proposed measurement model. For instance, the ratio of χ^2 to degrees-of-freedom (182.02/122) was used instead of χ^2 because χ^2 measure is too sensitive to sample size differences [56]. The χ^2/d.f. value is 1.49, which falls well within the recommended range of 1.0–2.0 by Hair et al. [56].

Table 2 – Demographic attributes of the respondents

Categories	Items	N[a]	%	Cumulative %
Applications[b]	Mobile emergency care systems	35	15.0	
	Mobile order systems	55	23.5	
	Mobile nursing systems	44	18.8	
	Mobile home care systems	13	5.6	
	Mobile health information systems	2	0.9	
	Mobile PACS	81	34.6	
	Others	4	1.7	100
Devices[b]	PDAs	35	22.7	
	Panel PCs	22	14.3	
	Tablet PCs	72	46.8	
	Notebooks	21	13.6	
	Others	4	2.6	100
Type of hospital[c]	Medical center	81	67.5	
	Regional teaching medical center	33	27.5	
	Regional medical center	1	0.8	
	Community teaching hospital	5	4.2	
	Community hospital	0	0.0	100
Ownership[c]	Public	4	3.3	
	Private	38	31.7	
	Juridical person	78	65.0	100
Position[d]	Physician	28	23.1	
	Nurse	64	52.9	
	Medical technician	29	24.0	100
Age[d]	Less than 20	0	0.0	
	20–29	68	56.2	
	30–39	44	36.4	
	40–49	9	7.4	
	50 or over	0	0.0	100

[a] N: means frequency.
[b] Respondents are allowed to choose more than one items in that category.
[c] There are three missing data in that category.
[d] There are two missing data in that category.

The goodness-of-fit (GFI) value of 0.86 is slightly less than the benchmark of 0.9 but very close to it, and the root mean square error of approximation (RMSEA) value of 0.064 falls well within the acceptable range of 0.05–0.08 by Hair et al. [56]. The results show that the measurement model has a good fit with the data based on other indices of fit such as normed fit index (NFI: 0.91), non-normed fit index (NNFI: 0.95), comparative fit index (CFI 0.96), and root mean square residual (RMSR: 0.039). Hence, we could proceed to evaluate the psychometric properties of the instrument in terms of reliability, convergent validity, and discriminant validity.

Table 3 – Model evaluation overall fit measurement

Fit indices	Recommended value	Value
χ^2	N/A	182.02
d.f.	N/A	122
χ^2/d.f.	≤3.00	1.49
Goodness of fit index (GFI)	≥0.9	0.86
Normed fit index (NFI)	≥0.9	0.91
Non-normed fit index (NNFI)	≥0.9	0.95
Comparative fit index (CFI)	≥0.9	0.96
Root mean square residual (RMSR)	≤0.05	0.039
Root mean square error of approximation (RMSEA)	≤0.08	0.064

Reliability and convergent validity of the constructs were estimated by Cronbach's α, composite reliability, and average variance extracted (see Table 4). Cronbach's α for all constructs were above the 0.7 threshold and ranged from 0.83 to 0.95. The composite reliability was estimated to evaluate the internal consistency of the measurement model and produced very similar results (ranged from 0.81 to 0.95). All were greater than the benchmark of 0.60 recommended by Bagozzi and Yi [57]. As depicted in Table 4, the average variance extracted for all measures exceeded the recommended 0.5 level (ranged from 0.59 to 0.87), which meant that more than one-half of the variances observed in the items were accounted for by their hypothesized constructs. This illustrates that all measures had strong and adequate reliability and discriminant validity.

Additional results of the multivariate test of the measurement model are indicated in Table 5. Convergent validity can also be assessed by the completely standardized factor loads and squared multiple correlations from CFA as presented in Table 5. All of the factor loads for the items in the research

Table 4 – Assessment of the construct reliability

Variables	Cronbach's α (>0.7)	Composite reliability (>0.6)	Average variance extracted (>0.5)
Compatibility	0.93	0.93	0.81
MHS self-efficacy	0.84	0.85	0.66
Tech support and training	0.83	0.81	0.59
Perceived usefulness	0.84	0.95	0.87
Perceived ease of use	0.95	0.85	0.66
Behavioral intention to use	0.94	0.94	0.84

model were greater than 0.7, whereas all of the squared multiple correlations were greater than 0.5 [56]. As a consequence, all constructs in the model exhibited adequate reliability and convergent validity.

4.3. *The structural model*

The SEM technique was used to examine the structural model so the effects among those six latent constructs were tested. MHS self-efficacy was explained by a variance of 56%, perceived usefulness with 70%, perceived ease of use with 65%, and the model as a whole explained 70% of the variance ($p<0.001$) in MHS acceptance, i.e., behavioral intention to use. Fig. 2 presents the standardized path coefficients that refer to the significant structural relationship among the tested variables. Most of the hypotheses were strongly supported except for hypotheses H5a and H5b. The data indicates that perceived usefulness has a direct effect on behavioral intention to use MHS (H1: $\beta=0.22$, $p<0.05$). While the perceived ease of use has a significant direct impact on behavioral intention to use MHS (H2a: $\beta=0.48$, $p<0.01$), it also has an indirect effect on behavioral intention to use through the mediator of perceived usefulness; meanwhile, PEOU also has an extremely strong effect on perceived usefulness (H2b: $\beta=0.69$, $p<0.001$). Consistent with our hypotheses, the results indicate that compatibility not only has a direct effect on behavioral intention to use MHS (H3a: $\gamma=0.27$, $p<0.05$) and perceived usefulness (H3b: $\gamma=0.32$, $p<0.05$), but also has strong significant and positive effects on both perceived ease of use (H3c: $\gamma=0.40$, $p<0.001$) and MHS self-efficacy (H3d: $\gamma=0.41$, $p<0.001$). Additionally, while MHS self-efficacy has direct effect on perceived usefulness (H4a: $\beta=0.34$, $p<0.05$) and has very strong effect on perceived ease of use (H4b: $\beta=0.47$, $p<0.001$), technical support and training has also an extremely significant direct impact on MHS self-efficacy (H5c: $\gamma=0.60$, $p<0.001$). Yet unfortunately, inconsistent with our hypotheses, the data shows that technical support and training has no significant effect on both perceived usefulness (H5a) and perceived ease of use (H5b). Worth noticing is that although the MHS self-efficacy has no direct effect on individual behavioral intent, it has a very strong indirect impact on behavioral intention ($p<0.001$).

Table 5 – Standardized factor loadings and individual item reliability

Item	Measure	Factor loading	$R^2>0.5$
Com1	Using MHS is compatible with most aspects of my work	0.88	0.77
Com2	Using MHS fits well with the way I like to work	0.94	0.88
Com3	Using MHS fits into my work style	0.88	0.77
MHSSE1	I could complete the job using MHS if there was no one around to tell me what to do as I go	0.86	0.74
MHSSE2	I could complete the job using MHS if I had never used a system like it before	0.82	0.67
MHSSE3	I could complete the job using MHS if I had used similar system before this one to do the same job	0.75	0.56
TST1	A specific person (or group) is available for assistance with MHS difficulties	0.76	0.58
TST2	Specialized instruction and education concerning software about MHS is available to me	0.77	0.59
TST3	Specialized programs or consultant about training are available to me	0.77	0.59
PU1	Using MHS would improve my performance in the healthcare practice	0.94	0.88
PU2	Using MHS would enhance my effectiveness in the healthcare practice	0.93	0.86
PU3	I would find MHS useful in the healthcare practice	0.91	0.83
PEOU1	Learning to use MHS would be easy for me	0.83	0.69
PEOU2	I would find it easy to get MHS to do what I want it to do	0.80	0.64
PEOU3	It would be easy for me to become skillful at using MHS	0.80	0.64
BI1	I intend to use MHS in my practice as often as needed	0.92	0.85
BI2	Whenever possible, I intend to use MHS in my practice	0.92	0.85
BI3	I estimate that my chances of using MHS in my practice are frequent	0.91	0.83

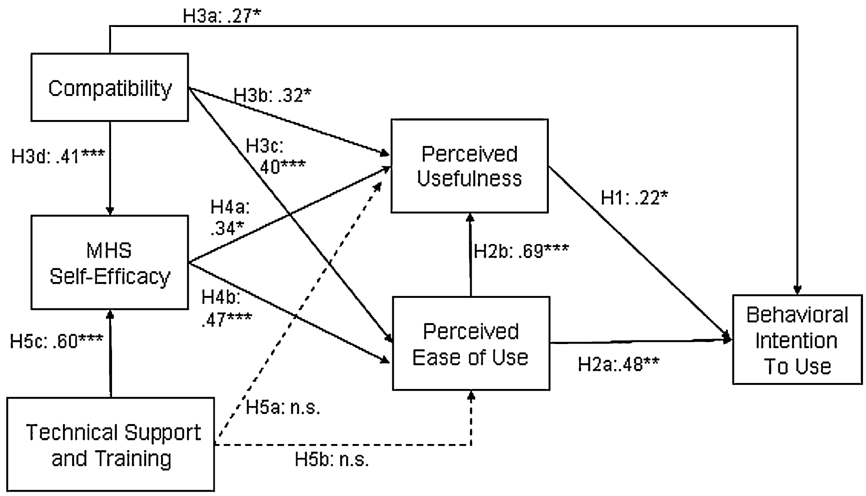

Fig. 2 – The empirical results of MHS. *Note:* Path coefficients (β and γ) are indicated in the path diagram. *Path is significant at the 0.05 level. **Path is significant at the 0.01 level. ***Path is significant at the 0.001 level. n.s. insignificant at the 0.05 level.

5. Discussions and conclusions

This study proposed a revised TAM that integrated compatibility, MHS self-efficacy, technical support and training with TAM to investigate what determined healthcare professional MHS acceptance and perception in the healthcare industry. The results indicated that perceived usefulness, perceived ease of use, compatibility, and MHS self-efficacy are important determinants to users' behavioral intent. Among these, the tests of the structural model indicated that the compatibility has the strongest total effect on the intention to use, whereas technical support and training was found no direct effects on both perceived ease of use and usefulness as well as no significant total effect on behavioral intent. In addition, both MHS self-efficacy and perceived ease of use also have very strong total effects on the behavioral intent; in contrast, perceived usefulness moderately affect the behavioral intent. Especially, technical support and training has significant indirect effects on both perceived usefulness and perceived ease of use though technical support and training has no significant direct impact on them. The results also demonstrate the importance of MHS self-efficacy in mediating the relationship of the technical support and training on MHS acceptance (i.e., perceived usefulness and perceived ease of use).

The descriptive statistics indicated that four respondents came from public hospitals and 116 came from private and juridical person hospitals, so the ratio of public hospitals to private and juridical person hospitals is ultimately small (approximately 0.03 only). We may infer that public hospitals indeed lagged behind private and juridical hospitals in MHS implementation and adoption. This suggests that public hospitals need to enhance their capability of planning and implementing new technologies to strengthen their competitive advantage at faster pace. Furthermore, the mean age is 29.6 with standard deviation 6.34 and the majority (92.6%) of respondents' age was from 20 to 39, tending to be young. This result is also consistent with Rigby's point of view: new and younger staff with less clinical experience is more fluent with the new technology [19]. While the PACS is used most frequently among the response, the tablet PCs are the major mobile equipment used for MHS. These could be the reason that physical size, weight, screen, or even electrical power and speed should be seriously considered while choosing suitable mobile devices in terms of gaining higher MHS acceptance. The implication is supported by Gebauer and Shaw's [23] study that asserted screen and keyboard size are the most significant factors for mobile application usage.

The testing results showed that healthcare professional's intention to use MHS can be explained or predicted through perceived usefulness and perceived ease of use [26,31,44], and the professional's perception of MHS usefulness is also influenced by the perception of MHS ease of use [26,31,32,44]. Our findings indicated that, consistent with prior studies [20,25], compatibility not only directly affects behavioral intent, perceived usefulness, perceived ease of use and MHS self-efficacy, but also has the most contribution (total effect) to professional's intention to use MHS. These imply that practice compatibility is the most significant antecedent of MHS success and must be taken into account while promoting and implementing MHS. As previous study stated [12], although healthcare professionals basically would like to use a mobile computerized patient records, the acceptance of such applications was rather low because the users demands might not be analyzed carefully and thoroughly. While MHS is more consistent with health care professionals' existing values, prior experiences and practice needs, they will not only feel more confident in using MHS, not needing to take a lot of efforts to learn or to reach familiarity with it, but also have higher perception of MHS advantage. Therefore, they will be more likely to use MHS.

Besides developing useful and easy to use healthcare systems, mobile IT/IS designers should also pay more attention to user requirements analysis to determine their expectations and requirements for mobile healthcare application content. The relevant materials and functions can then be incorporated into the systems. Only when participants have higher perceptions in compatibility with their previous or current practice processes there is a higher possibility to achieve successful MHS acceptance. Additionally, an ease-of-use and useful design is also an important criteria for developing and adopting MHS.

These findings show that technical support and training have a significant effect on MHS self-efficacy, which is consistent with other studies [42–44,51]. For instance, the results of Hypothesis (H5c), coherent with Hasan's study [51], demonstrate that technical support and valuable training programs will efficiently increase MHS self-efficacy beliefs. Horan et al. [25] also pointed out the significance of staff training for implementing and using the online system in clinical practices; Torkzadeh and Van Dyke [42] reported that technical related support and training significantly enhanced Internet self-efficacy.

Contrary to the Hypotheses H5a and H5b, technical support and training was found to have no significant effects on both perceived usefulness and perceived ease of use which are partially supported by literature [50]. Prior study showed that intra-organizational computing support and training had no influence on perceived system ease of use and internal and external computing support also had no effect on perceived usefulness for technology acceptance in a small firm context. The reason can be that the majority of IT/IS applications are designed user friendly with an intuitive interface to considerably enhance the functionality of systems, particularly ease of use. Scarborough and Zimmerer [58] asserted that the launch of any new technology will progressively go through the three stages: substitution, adaptation and revolution. In the initial stage – substitution – people generally employ the new technology as a substitute for existing appliances to implement the same tasks more effectively. In stage 2 – adaptation – people ascertain that they can do new things via the new technology. In stage 3 – revolution – people begin to use the new technology in new ways, doing things that have never been done before. Hence, mature innovation technology has reduced the user interface problems while users are equipped with essential skills and confidence. The other plausible explanations can be as follows:

(1) All hospitals involved have implemented computerized healthcare IT/IS, so they will be equipped with essential computing skills and confidence in using mobile devices. Moreover, the majority (92.6%) of respondents is between the ages of 20 and 39, who are younger and have more advanced computing skills; so they are easier to accept new mobile IT/IS.
(2) All hospitals involved are actually or partially implementing MHS; therefore, specific or related MHS training has already been provided to those professionals before implementing MHS.

As mentioned previously, the technical support and training have strong direct positive impact on MHS self-efficacy; thus, MHS self-efficacy is an important mediating factor in implementing MHS acceptance. Given the appropriate technical support and training courses can raise professional's MHS self-efficacy perceptions and lead to great MHS adoption [51]. In other words, the availability of technical support and training in the healthcare organization are of crucial importance to MHS success. Sufficient and proper technical support and training will positively enable individuals to solve ambiguities surrounding the new IT/IS and strengthen self-efficacy of MHS usage.

Conversely, although technical support and training do not influence both perceived usefulness and perceived ease of use, there are some significant practical considerations. First, it seems reasonable to infer that either the organizations may not provide related MHS technical support and training efficiently to professionals or there are some problems with the lack of satisfaction. The latter may comprise insufficient resources such as mobile equipment, potable systems, technology infrastructure, etc. Secondly, the goals and objectives of implementing MHS may not be clearly and adequately understood by each medical staff member. Medical organizations must exactly and thoroughly educate their staff about the goals and advantages of implementing MHS. Insufficient comprehension will decrease individual's motivation to use new IT/IS and finally result in unsuccessful innovations adoption.

There is an increasing awareness of what benefits can be obtained from an IT investment in healthcare setting, such as improvement of care quality and patient satisfaction, decrease of clinical errors, as well as up-to-date patient and healthcare information. The explosion of mobile IT/IS in supporting health care and services has made it extremely important to understand the determinants essential to MHS acceptance by health care professionals. Owing to resource constraints, while the findings of this study apply only to mobile healthcare setting, the generalizability of the findings to other industries needs to be examined in further study. Moreover, the proposed model variables explained 70% of the variance in behavioral intention to use MHS, further study is needed to explore extra significant antecedents of new IT/IS acceptance for mobile healthcare. Such as privacy and security issue, system and information quality, limitations of mobile devices (i.e., weight, size, electrical power requirements, etc.); the above may be other interesting factors for implementing mobile healthcare and could be conducted by qualitative research. These results provide initial insights into factors that are likely to be significant antecedents of planning and implementing mobile healthcare to enhance professionals' MHS acceptance.

Although this study provides interesting insights into the factors affecting the intention to use MHS, there are some limitations. First, this study did not measure the change in user reactions over time because prior studies suggested that individual perceptions in compatibility and self-efficacy to behavioral intent may improve over time with increased system experience [34,35,45]. The introduction of new IT/IS will take time so it seems not reasonable to employ a new IT/IS and measure the effects immediately. Yet, our study provides useful insights into understanding determinants of implementing new MHS in the health care setting at this early stage. Second, the exposure of MHS is still in its infancy in Taiwan as well as the types and standards of MHS applications are still limited. Insufficient understanding of MHS and limited applications will lead to a lower user intention to use it.

Third, this study was conducted via snowball and convenient sampling due to our specific subjects and low mail survey response rates from healthcare industry. The phenomenon results from their high professional autonomy and organizational policies. The challenge is the limitation and response rate in mail surveys from IT/IS users in the complicated health care industry. In addition, our subjects were those who used MHS as voluntarily with self-reported measures. The sampling method employed here could have inadvertently introduced some selections bias in the choice of participants. Subject motivation may be a potential issue here as souvenir is a modest incentive. Therefore, our samples may not be the representative of the entire population due to possible sample selection bias. However, self-reported measures have been viewed as a relative indicator.

What the research has learned

What was known before the study?

- Mobile communication technologies have been dramatically and widely applied in ordinary businesses.
- We expect that the healthcare industry will soon thrive efficiently on mobile information technologies and systems. However, applications for mobile computing in health care are still under development.
- The healthcare industry, conventionally, is recognized as having lagged behind other industries in the use and adoption of new information technologies and information systems.

What the study has added to the body of knowledge?

- The study presented a revised technology acceptance model to examine what determines MHS acceptance by healthcare professionals.
- The results indicated that compatibility, perceived usefulness and perceived ease of use significantly affected healthcare professional behavioral intent. MHS self-efficacy had strong indirect impact on healthcare professional behavioral intent through the mediators of perceived usefulness and perceived ease of use.
- Technical support and training has strong impact on MHS self-efficacy while no significant effect on both perceived usefulness and perceived ease of use. Some implications have been discussed in the study.

Acknowledgements

We gratefully acknowledge the constructive comments and suggestions provided by the editor and reviewers. The study presented in this paper was partially supported by a grant form the National Science Council of Taiwan (Project no. NSC 93-2416-H-110-015) and aim for the Top University Plan of the National Sun Yat-Sen University and Ministry of Education, Taiwan.

Appendix A. Overall goodness-of-fit measures for structural equation modeling in this study

See Table A.1.

Appendix B. Structural coefficients

See Table A.2.

Table A.1

Goodness-of-fit	Description
Goodness of fit index (GFI)	GFI is a measure of the relative amount of variances and covariances jointly accounted for by the model. GFI is independent of the sample size and relatively robust against departures from normality [59]: $GFI = 1 - \frac{tr[(\hat{\Sigma}^{-1}S - I)^2]}{tr[(\hat{\Sigma}^{-1}S)^2]}$ for maximum likelihood
Normed fit index (NFI)	NFI is a measure ranging from 0 (no fit at all) to 1.0 (perfect fit). It is a ratio of the difference in the χ^2 value for the proposed model and a null model divided by the χ^2 value for the null model [60]: $NFI = \frac{\chi^2_{null} - \chi^2_{proposed}}{\chi^2_{null}}$
Non-normed fit index (NNFI)	NNFI uses a similar logic but adjusts the NFI for the number of degrees of freedom in the model [61]: $NNFI = \frac{(\chi^2_{null}/d.f._{null}) - (\chi^2_{proposed}/d.f._{proposed})}{(\chi^2_{null}/d.f._{null}) - 1}$
Comparative fit index (CFI)	CFI is based on the non-central parameter, which can be estimated as χ^2–d.f. It also ranges between 0 and 1, with values exceeding 0.90 indicating a good fit to the data [62]: $CFI = 1 - \frac{\chi^2_{proposed} - d.f._{proposed}}{\chi^2_{null} - d.f._{null}}$
Root mean square residual (RMSR)	RMSR is the square root of the mean of the squared residuals—an average of the residuals between individual observed and estimated variance and covariance terms [59]: $RMSR = \sqrt{\frac{2\sum_{i=1}^{k}\sum_{j=1}^{i}(s_{ij} - \hat{\sigma}_{ij})^2}{k(k+1)}}$
Root mean square error of approximation (RMSEA)	Similar to RMSR, RMSEA is based on the analysis of residuals, with smaller values indicating a better fit to the data [63]: $RMSEA = \sqrt{\frac{(\chi^2_{proposed}/d.f._{proposed}) - 1}{n-1}}$

$\hat{\Sigma}$ = the estimate of a structured covariance matrix, S = an unbiased sample covariance matrix. I = an identity matrix, tr[ ] = the trace of the matrix, i.e., the sum of the diagonal elements, $\chi^2_{proposed}$ = the non-centrality parameter for the model tested, $d.f._{proposed}$ = the degrees of freedom for the model tested, χ^2_{null} and $d.f._{null}$ are the non-centrality parameter for the null model. S_{ij} = an element in the observed covariance matrix, $\hat{\sigma}_{ij}$ = an element in the fitted covariance matrix (estimated), k = the total number of observed variables in the model, n = sample size.

Table A.2

Coefficients	Description
Beta (β)	Structural coefficients relating latent dependent variable to latent dependent variable
Gamma (γ)	Structural coefficients relating latent independent variable to latent dependent variable

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