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# Understanding Pharmacists' Intention to Use Medical Apps

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*Abstract*
*Objectives: The goal of this study is to investigate pharmacists' perception towards mobile medical apps use in pharmacy practice and to explore both the enabling and inhibiting factors that govern the adoption of this Mobile Health (mHealth) tool.*
*Methods: This study employed quantitative research methodology to examine the relationships between key constructs and pharmacists' intention to use medical apps. Multi-items questionnaire was developed to draw participation of pharmacists from various fields of practice in Malaysia. Quantitative data was analyzed using partial least squares (PLS) modeling statistical technique.*
*Results: The findings provided strong empirical support for six positive determinants (perceived usefulness, perceived ease of use, result demonstrability, subjective norm, compatibility, facilitating conditions) and two negative (security, resistance to change) determinants of intention to use medical apps. The proposed model had good predictive relevance to infer actual medical apps use.*
*Discussion: Pharmacy informaticists are able to manipulate the key factors presented in the research model in such a way to maximize the adoption of medical apps amongst the pharmacists. The study showed that the usefulness of the apps along with their reliability were the most effective influence on intention to use. Pharmacists were worried about the data security which could potentially hinder the adoption.*
*Conclusions: This study represents a pioneer dual-factor model technology adoption study. It has shed light on the aspects where decision makers from managerial stand-point are able to manipulate to achieve maximum diffusion of mobile technology within the health institution.*

***Keywords: Mobile Health; Medical Apps; Technology Adoption; Pharmacoinformatics; Barriers; Health Informatics***

## 1 Introduction

Health care delivery is moving rapidly from a world of patient influx to a world of data influx, transforming patients' engagement within the health care system. Long-hour waiting to doctor's appointment, having to search for pharmacies to get hand-written prescriptions filled, hunting down medical records tiresomely, and being left in the dark about health care bills are all inconveniences that will soon be historical. It was estimated that in United States 1.8 million patients would be treated via telehealth by 2017[1]. It has been shown that health care providers are increasingly using smartphones and tablets to access patient data by 68% more in 2013 than in 2012[1]. Subsequently, mobile health technology holds a potential for more efficient, more competent and more cost effective processes in health care, especially with increasing popularity of mobile apps use within the emerging Mobile Health (mHealth) entity. It is believed that health care providers, as well as pharmaceutical industry, will supplant mobile phone industry as the primary distributors for mHealth related mobile medical apps[2].

Today, options are available for pharmacists at point of clinical decision-making to identify drug interactions, look up for drugs dosing and side effects as well as to help patients managing their disease via mobile medical apps such as medication reminder apps and patient education apps[3]. Pharmacists are able to perform medication review round the clock and at point of care with the decision support abilities provided by technologies. Various studies have shown significant reduction in medication dispensing errors, drug-drug interactions, adverse drug reactions and costing corresponding to adoption of IT in pharmacies[4-9]. The arrival of mobile medical apps technology is postulated to change several facets of pharmacy practice, such as dispensing system, pharmacy automation, electronic prescribing, electronic health records, and pharmacy tracking software[10]. Many pharmacies are now trending to develop programs and apps based on monitoring and supervision to support patient-centred disease management, for example prescription and medication reminders apps, blood pressure and sugar level monitoring apps[11].

Whilst the patients are eagerly showing their interests in these new technology tools[12] that allow them to manage their own health, acceptance of medical apps by health care providers remained in shadow. Despite the fact that innovations in information system have greatly improved the quality and productivity within various industries, reports have shown that slight progress has occurred in health care industry in terms of the adoption of Health Information Technology (HIT)[13]. Many health care organizations have realised that successful implementation of HIT such as medical apps and its related mobile technology relies remarkably on the acceptance and adoption by its end users. In fact, it is not uncommon that rejection of HIT by health care professionals is reported from time to time, leading to huge financial lost to health care institutions and substandard patient care[14-16]. Besides cost issues, management, planning and corporation issues, and software issues, "the 'human element' is critical to health IT implementation"[17]. Thus, it is important to identify the characteristics and factors that influence acceptance and rejection of medical apps use by pharmacists.

### 1.1 Proposed Research Model

In this study, medical apps were referred to as a new mHealth tool that complements HIT. Research model (Figure 1) tested in this study was developed and conceptualised based on integrated concept of Technology Acceptance Model (TAM) and its extended versions[18, 19], Theory of Planned Behaviour (TPB)[20], Innovation Diffusion Theory (IDT)[21] and Theory of User Resistance[22, 23]. These concepts served to explain the relationship between user's attitudes, perception, beliefs and eventual adoption of certain technology system.

Behavioural Intention (BI) was an appropriate dependent variable chosen for both hypothetical and practical reasons. It was theoretically permissible to examine technology acceptance using BI because prior studies have suggested that there was a strong link between behavioural intention and targeted behaviour[24, 25]. Pragmatically speaking, medical apps development and implementation are still in its early stage in a lot of countries and organizations, it is therefore difficult to estimate actual system use since the system is yet to exist. As such, it is desirable to measure end user's intention to use the system during design and early implementation stage[26]. Examining the users' intention was also most appropriate in this study because this was a cross-sectional design that was based on the measurement of end users contemporary beliefs at the point the data gathering[27]. Furthermore, variances explained by BI in many health informatics studies were reasonably high[28].

### 1.2 Acceptance Factors

User acceptance studies on mobile devices usage by pharmacists in their practice traced back earlier in 1990's when Personal Digital Assistants (PDA) were popular and before the emergence of more advanced devices such as smartphones and its related mobile apps. Literature revealed that pharmacists had been using PDA, which functions as a personal information manager along with related software, to carry out their daily tasks in workplace. These tasks included documentation of various pharmacist interventions[29] that include dose adjustment[30], treatment recommendation, drug-related problems[31], pharmacy cognitive services[32] and clinical pharmacy services[33, 34]. It was evident that PDAs offered highly efficient and portable substantial means of documenting pharmacy services in various settings[35]. Table 1 summarizes various technology adoption studies in examining pharmacists' intention to adopt these technologies.

### 1.3 Perceived usefulness and perceived ease of use

TAM was first developed by Davis during 1980's in an attempt to explain and predict user's intention to use computer technology[18]. It was based on the study of their attitudes towards the systems. The basic concept of the model was derived from Theory of Reasoned Action (TRA)[36], which stated that behaviours were guided by

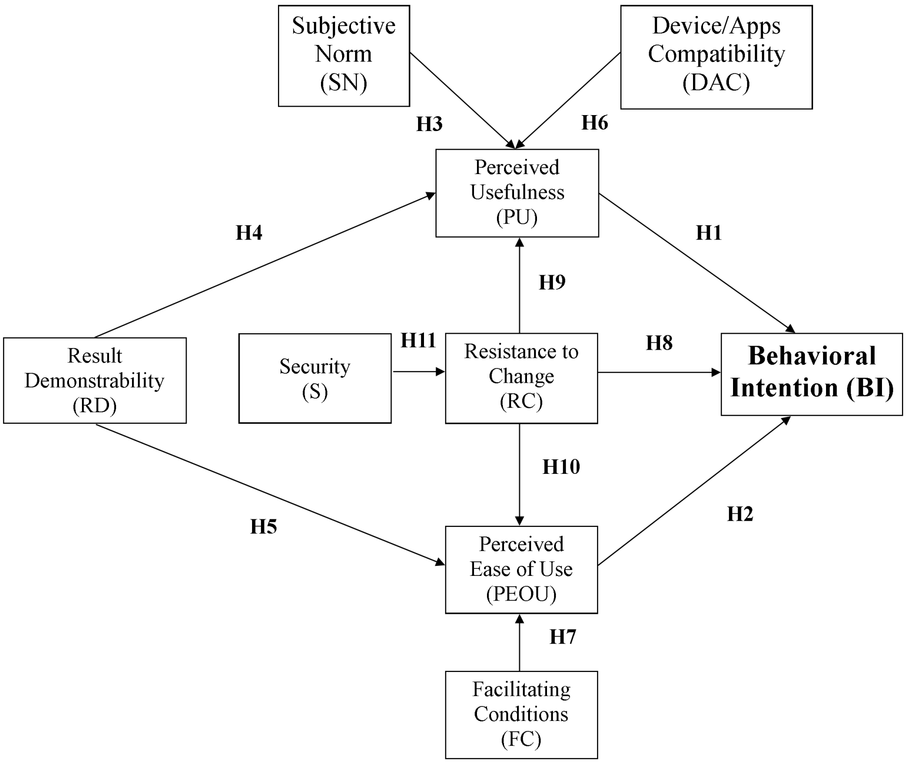


*Figure 1: Proposed research model*

someone's intention that was shaped by his/her attitudes which in turn were influenced by one's beliefs. Over the years, TAM had become a well-established robust model for predicting user acceptance, it had progressed substantially resolving its limitation and development of a few upgraded theoretical models extended from the two key constructs namely perceived usefulness and perceived ease of use. Improvised version of the original TAM model includes TAM 2[19, 37], Unified Theory of Acceptance and Use of Technology (UTAUT)[19], and TAM 3[38]. Although the model was not developed empirically to examine user acceptance of IT systems in health care industry, many studies have been conducted to test TAM within the context of health[28]. In this study, researchers have incorporated two key constructs from original TAM model into the proposed research model in determining pharmacists' intention to use medical apps. Perceived Usefulness is "the degree to which a pharmacist believes that using mobile medical apps would enhance his or her job performance", whereas Perceived Ease of Use is "the degree to which a pharmacist believes that using mobile medical apps would be free of effort".

Therefore, we hypothesized that:

- H1. Perceived Usefulness (PU) has positive effect on intention to use medical apps.
- H2. Perceived Ease of Use (PEOU) has positive effect on intention to use medical apps.

### 1.4 Subjective norm and result demonstrability

In 2000, TAM 2 was developed by Venkatesh & Davis as an effort to better understand the determinants of perceived usefulness, which has consistently being a strong contributing factor of intention to use a system[37]. In TAM 2, social influence and cognitive instrumental processes have replaced the attitude component as two new elements. The social influence processes were operationalized through subjective norm and image; whereas the cognitive instrumental processes were operationalized through job relevance, output quality, result demonstrability and perceived ease of use. In this context, the definition of Subjective Norm is "the degree to which an individual perceives that most people who are important to him think he should or should not use the system." In one study conducted in 2009 to examine pharmacists' adoption of PDA, subjective norm and result demonstrability were found to be strongly related to intention to use PDA[39]. The findings were consistent with the theory that individuals emulated behaviours of the other in social groupings based on what they observed[49]. This suggested that social norm (subjective norm) played a significant role in affecting pharmacists' decisions indirectly because the opinions and suggestions by peers were highly sought after. These suggestions pertained to the degree of usefulness the new tools were in enhancing job performance. Hence, we hypothesized that:

- H3. Subjective norm has positive effect on perceived usefulness.

On the other hand, Result Demonstrability refers to "the degree to which pharmacist believes that the results of using a system are tangible, observable, and communicable". This suggests a positive relationship between result demonstrability of medical apps and perception of pharmacists on its usefulness. Furthermore, result demonstrability is theorized to affect perceived ease of use directly because the extent to which the results of using medical apps is demonstrable indicates that an individual is able to and confident to perform a behaviour. Therefore, they are more likely to make internal attribution in performing certain tasks[50]. We hypothesized that:

- H4. Result demonstrability has positive effect on perceived usefulness.
- H5. Result demonstrability has positive effect on perceived ease of use.

### 1.5 Compatibility and facilitating conditions

Innovation of Diffusion Theory (IDT) is another popular theory trying to explain how and why innovations diffuse across cultures[21]. The theory includes four main aspects for consideration if a new technology is to become popular within certain culture and field. These are innovation, communication style, steps in decision-making and social system. Researchers have used IDT as an extra component to supplement TAM's model in studying the acceptance of technology. It is also highly recommended to apply IDT in health care settings[51]. In fact, innovation attributes was deemed to affect end-users' perception and attitude towards an innovation before actual adoption happens[52]. Mobile devices and related apps must be able to integrate into the existing workflow in such a way that pharmacists would perceive that they are useful and effortless. In this study, researchers focused on the innovation characteristics of mobile technology, as well as organizational and environmental factors, which could potentially having impact on the speed of innovation adoption. In this context, organizational and environmental factors were grouped under Facilitating Conditions, which was one of the key constructs proposed in Unified Theory of Acceptance and Use of Technology (UTAUT) model[19].

| **Study** | **Technology/Application Studied** | **Population Studied and Setting** | **Key Constructs** |
|---|---|---|---|
| Dasgupta et al., 2009[39] | Personal Digital Assistant (PDA) | Pharmacists from hospitals and community in US | Perceived usefulness, Perceived Ease of Use, Subjective Norm, Voluntariness, Image, Job Relevance, Quality Output, Result Demonstrability, Attitude |
| Fleming et al., 2013[40] | Prescription Drug Monitoring Programs (PDMP) via web portal | Community Pharmacists in Texas, US | Attitude, Perceived Obligation, Subjective Norm, Perceived Behavioural Control |
| Gavaza et al., 2013[41] | Prescription Drug Monitoring Programs (PDMP) | Members of the Virginia Pharmacists Association | Attitude, Subjective Norm, Perceived Behavioural Control, Past Utilization Behaviour, Perceived Moral Obligation. |
| Gavaza et al., 2012[42] | Adverse Drug Reaction Reporting | Pharmacists from Texas, US | Attitude, Subjective Norm, Perceived Behavioural Control |
| Gavaza et al., 2011[43] | Serious Adverse Drug Reaction Reporting to FDA | Practicing Texas Pharmacists | Attitude, Subjective Norm, Perceived Moral Obligation, Perceived Behavioural Control |
| Herbert et al., 2006[44] | Medication Therapy Management Services | Community Pharmacists from Iowa, US | Theory of Planned Behaviour |
| Holden et al., 2012[45] | Bar-coded medication dispensing and administration technology (BCMA) | Pharmacists and pharmacy technicians at a hospital in Midwest U.S | Perceived Usefulness for Self, Perceived Usefulness for Patient, Perceived Social Influence, Satisfaction with System |
| Rahimi and Timpka, 2011[46] | Integrated Electronic Prescribing System | Pharmacists in Sweden | Usefulness and Usability on work efficacy, Barriers to system use |
| Siracuse and Sowell, 2008[47] | Personal Digital Assistant (PDA) | PharmD students at two Universities | Perceived usefulness, Perceived Ease of Use, Subjective Norm, Image, Compatibility, Result Demonstrability, Attitude, Perceived Behavioural Control |
| Smith and Motley, 2010[48] | Electronic Prescribing | Pharmacists in US | Technological Sophistication, Operational Factors |
| | | | and Maturity Factors |

*Table 1: Health Information Technology (HIT) adoption studies relevant to the field of pharmacy practice*

Its definition is given as "the perception that organizational and technical infrastructure exists to support using medical apps". This includes the availability of resources, training, network connectivity, technical and financial support, and organization policies. Therefore, we hypothesized that:

- H6. Device/apps compatibility has positive effect on perceived usefulness.
- H7. Facilitating condition has positive effect on perceived ease of use.

### 1.6 Resistance Factors

In one of the recent studies, technology system usage theory was reintroduced with a dual factors model that was moderated by both enablers (variables that explain acceptance) and inhibitors (variables that explain resistance) [22]. This appeared to be the first approach in the field in trying to explain and differentiate technology acceptance and technology resistance. Broadly speaking, resistance can be viewed as 'one-side' or asymmetric effect, which suggests that inhibitors are not reasonably the opposite of enablers. As such, occurrence of barriers damages IT adoption however absence of barriers does not certainly promote IT usage[23]. As pointed out, different models of resistance, which is not the same as acceptance models, are required because it is believed that the better resistance theory is in explaining system usage, the better the implementation strategies and outcomes it could lead to. Technology adoption studies should avoid treating user resistance as a black box and should be opened for theoretical explanations[53]. Taking into this as consideration, the study model has incorporated the potential inhibition elements that could possibly hinder the adoption of medical apps.

### 1.7 User resistance

User resistance has been identified as one of the top challenges for the implementation of large scale information systems[54]. The importance of integrating the concept of user resistance in all information technology adoption studies, HIT studies included, is well established[55]. An interview study conducted during the implementation of pharmacy bar code dispensing technology in a hospital on pharmacy staffs regarding their perception about the potential barriers and facilitators toward the system has identified three major barriers within: process, technology and user resistance[56]. During early stage of the implementation, pharmacy staffs did not have adequate training and time to adapt to the changes of workflow, which could have resulted in low adoption because they perceived that the system was not useful. As for the technical issues, the system was not functioning properly due to problems raised from both hardware and software. More importantly, pharmacy staffs themselves did not have positive perceptions about the new technology since they felt overwhelmed by the changing roles and perceived lack of communications.

The definition of resistance used in literatures varies. Typically, resistance is associated with low levels of use, by a lack of use or by dysfunctional e.g. harmful use[57]. However, according to the semantic analysis performed in one study, concept of resistance phenomena consisted of five major components: resistance behaviours, object of resistance, perceived threats, initial conditions, and subject of resistance[58]. Interestingly, user rejection is different from user non-adoption within the context of resistance behaviours. Rejection usually refers to a conscious decision made by the users to not use a particular system, as opposed to non-adoption which leaves the door open for future use[22]. This study has undertaken the dual-factor approach with the following hypotheses:

- H8. Resistance to change has negative effect on intention to use medical apps.
- H9. Resistance to change has negative effect on perceived usefulness.
- H10. Resistance to change has negative effect on perceived ease of use.

### 1.8 Security

Recently, concerns over mobile apps data security are on the rise. Studies on health and fitness apps have found out that as many as 26% of free apps and 40% of paid apps do not have privacy policy at all[59]. Worse still is that almost none and only one paid apps has features designated for data encryption for safe data communications between users and developers or third-party advertising services[60], not to mention also some apps are merely malicious with devious intentions. No doubt that this has direct impact on intention to use medical apps given that end users are increasingly cautious in selecting useful medical apps that are safe over to use over the internet or intranet network. In one focus group study, pharmacists have indicated that they were worried and concerned about this matter because the use of medical apps might render them to higher legal liability as a result of unintentional disclosure of patient privacy and confidentiality[61]. The same is applied to safe use of these open-source apps whereby they are too vulnerable to any sort of cyber security threats. Some opinions suggest that the apps are still not ready yet for full integration into current health care system. As a result, pharmacists are not favourable in using the medical apps when it involves collection and dissemination of patient health related data. Instead, pharmacists would have chosen to remain working with existing system rather than taking risk in trying out the innovation. It was therefore hypothesized that:

- H11. Potential security issues have negative effect on intention to use medical apps.

## 2 Methods

### 2.1 Instrument Development

Multi-item questionnaire items were developed in this quantitative study. Eight constructs were identified from relevant prior studies [18, 19, 23, 39, 62, 63]. We hypothesized six constructs as having positive impact and two constructs were having negative impact on the overall intention to use medical apps by pharmacists (dependent variable) (refer to Figure 1). The definitions of constructs were adapted with changes in wording that suited pharmacists' usage of medical apps.

Table of specification method was employed to operationalize constructs and to generate item pool related to the constructs that were not able to be observed directly[64]. As a result, researchers have generated 40 items from eight constructs with an average of five items each giving the expected final multi-item scale of measurements. Following this, researchers performed several reviewing activities to refine the preliminary draft of the instrument items. Firstly, researchers reviewed the items and read aloud to check if sentences flow coherently and to identify problems in wording and sentence structure. Secondly, three instrument construction experts, who were faculty members from two local tertiary education institutions, reviewed the table of specification. Thirdly, one expertise in writing who was the faculty member from an English learning centre reviewed the use of English language. Lastly, Q-sorting method[65] was adapted in this study to refine the item pool in view of the lengthiness of the questionnaire. The final questionnaire contained 25 items. Local ethics committee has reviewed and approved the questionnaire.

### 2.2 Pretest

The researchers have further tested the questionnaire for item consistency and item reliability. We have initiated a pilot study involving 50 potential participants. Based on the responses from this group of pharmacists, evidence of item reliability i.e. Cronbach's alpha coefficients values were computed statistically using IBM SPSS statistic software version 21. The Cronbach's alpha values of constructs obtained were all within acceptable range (above 0.60), except Subjective Norm (SN) and Device/apps Compatibility (DAC) both having questionable alpha value of 0.598 and 0.573 respectively (Table 2). Upon examination on the item-total correlations, it was discovered that item SN_3 and item DAC_1 had poor inter item correlation (below 0.40)[66]. Thorough examination of the original item statements revealed that both items were poorly constructed and were irrelevant to the constructs. It was decided that these two items were removed, and the resultant new Cronbach's alpha value had improved significantly to 0.735 and 0.935 respectively. The total number of items derived from the constructs had been reduced to 23; one item was included for Behavioural Intention (BI) thus making 24 items in the finalized version of questionnaire (refer to Appendix).

### 2.3 Data Collection

The population of interest for the purpose of this study was the pharmacists who were practicing in their professional fields at the time of data collection. The sample was included pharmacists who were from hospital pharmacies, community pharmacies, pharmaceutical industries, or any other related fields. Since "intention to use" was the key measurement variable, it was not mandatory for them to own any of the mobile devices or had any experiences in medical apps usage.

Researchers sent out self-administrated questionnaires via two major routes: paper-based and electronic-based (include web survey engine and emails). The period of data collection encompassed 6 months period from May 2013 to November 2013. Initially, we collected 453 sets of questionnaires from various states in Malaysia. The data was then examined and filtered for any incompleteness, leading to a final valid data set of N=414 (81.7% collected via paper-based, 13.5% via web survey engine, and 4.8% via emails).

Among the respondents, 58% and 42% of them were male and female respectively, with median age of 30 years old. The dataset represented the four key stakeholder groups identified: hospital pharmacists (76%), community pharmacists (14%), industry pharmacists (6%) and others (4%). When asked about ownership of mobile devices such as smartphones and tablets, 76% of respondents reported to own smartphone alone but only 3% own tablets only. However, 18% have reported to own both of the devices and 3% did not own any of these devices. Most importantly, 88% of the respondents have used medical apps in their work voluntarily, and they have spent about 3 hours on average every week in using them. Top ranking medical apps used included drug reference apps (64%) and disease diagnostic tools (28%).

### 2.4 Data Analysis

Partial Least Squares (PLS), which is a variance-based structural equation modeling (SEM) technique, was used to assess the proposed theoretical model using SmartPLS 3.0 (M3) Beta computer software[67]. The exploratory nature of PLS technique was suitable in this study because both the theoretical knowledge and fundamental knowledge for pharmacists' adoption of medical apps were limited. In addition, this technique was employed because literally there was no requirement for data distribution assumptions to be made and PLS allowed working with small sample size[68].

## 3 Results

### 3.1 Path Coefficient Analysis

SmartPLS[67] was used to compute the path estimations in the structural model and the results were shown in Table 3. This was followed by performing bootstrap analysis to assess the statistical significance of the path coefficients. This was one of the approaches for estimating confidence intervals for PLS estimation that used the N bootstrap estimates for each parameter of interest to calculate the standard error and associated t-test[69].

From the initial set of paths, all 11 hypotheses had demonstrated expected path coefficient values that matched their hypothesized effects. Bootstrap analysis revealed that one hypothesis was significant at 0.95 level, two at 0.99 level and seven at 0.999 level. One hypothesis (H8) has shown p value greater than 0.005 (Table 3). Figure 2 showed the significant path for the proposed research model. All hypotheses were supported with statistical significant impact, except for the effect of resistance to change on behavioural intention (H8). Overall, H11 had the strongest correlation and H8 had the weakest correlation.

### 3.2 Model Evaluation

PLS structural model is mainly evaluated by Goodness-of-Fit (GoF)[70], and by using the Stone-Geisser Q-square test for predictive relevance [71, 72].

#### 3.2.1 Stone-Geisser Q-square test (Q2)

Q2 test represents a measure of how well observed values are reconstructed by the model and its parameter estimates. Models with Q2 greater than zero are considered to have predictive relevance, higher positive Q2 values are indicative of higher predictive relevance of such models[69]. The process involves omitting or "blindfolding" one case at a time and re-estimating the model parameters based on the remaining cases. The omitted case values are then predicted on the basis of the newly estimated parameters of the remaining cases.

In this research model, cross-validation test that was used to evaluate both measurement model and structural model were computed. The blindfolding results using omission distance G=7 are shown in Table 4. Cv-redundancy (F2) values, which served as an quality indicator of the structural model, were examined because it measured the aptitude of the model to predict endogenous variables from the exogenous variables[70]. F2 values for all four endogenous variables were greater than zero, with highest value of 0.2602 for BI, and lowest value of 0.0963 for PEOU. Overall, the predictive relevance of the model was demonstrated for all endogenous constructs.

#### 3.2.2 Goodness-of-Fit (GoF) Index

To validate the PLS model, Global Criterion of Goodness-of-fit (GoF) was adopted[70]. This index is the geometric mean of the average communality and the average R2. GoF index must be >0.36 to suggest a good model with reliable predictive ability (large effect size)[70, 73]. In this model, the GoF index value was 0.4202 (Table 5), suggestive of good predictive reliability of the model.

## 4 Discussion

### 4.1 Perceived Usefulness

Perceived usefulness has demonstrated strongest correlation on behavioural intention to use medical apps by pharmacists. The outcome is consistent with a lot of HIT adoption studies conducted in other health care professionals. Medical apps have paved ways to improve quality of care, patient satisfaction and safety, time saving and cost reduction reflecting the digital age we live in. Changing the way health care is delivered, medical apps are popular among health care professionals and are perceived as useful in their job performances. This is mainly due the ability of this sophisticated mobile technology to deliver simple, personalised, effective and

| Construct | Items | Cronbach's Alpha | Item-Total Correlation | Original items | Retained Items |
|---|---|---|---|---|---|
| Perceived Usefulness (PU) | | 0.751 | | 3 | 3 |
| PU_1 | Using medical apps on mobile devices improves my job performance. | | 0.541 | | |
| PU_2 | Using medical apps on mobile devices enables me to accomplished tasks more quickly. | | 0.627 | | |
| PU_3 | Using the medical apps will increase my productivity. | | 0.596 | | |
| Perceived Ease of Use (PEOU) | | 0.753 | | 3 | 3 |
| PEOU_1 | My interaction with medical apps on mobile devices is clear and understandable. | | 0.637 | | |
| PEOU_2 | It is easy for me to remember how to perform tasks using medical apps. | | 0.694 | | |
| PEOU_3 | It would be easy for me to become skilful at using the system. | | 0.436 | | |
| Subjective Norm (SN) | | 0.598 (.735)* | | 3 | 2 |
| SN_1 | I will use medical apps if people who influence my behaviour think I should use it. | | 0.518 | | |
| SN_2 | The trends of smartphone usage will influence my decision to use. | | 0.532 | | |
| SN_3** | Using medical apps on mobile devices representing a status symbol in my work. | | 0.208 | | |
| Result Demonstrability (RD) | | 0.773 | | 3 | 3 |
| RD_1 | The results of using medical apps are apparent to me. | | 0.572 | | |
| RD_2 | I have no difficulty telling others about the results of using medical apps. | | 0.73 | | |
| RD_3 | I am confident to make decision based on information obtained through medical apps. | | 0.557 | | |
| Facilitating Conditions (FC) | | 0.667 | | 3 | 3 |
| FC_1 | I will use medical apps if supports are easily reachable. | | 0.601 | | |
| FC_2 | Organizational policy and support to use medical apps influence my decision to use. | | 0.458 | | |
| FC_3 | I will use medical apps if all external factors are favourable. | | 0.391 | | |

*Table 2: Cronbach's alpha and item analysis of measurement items in pilot testing. * = Cronbach's alpha value after item was omitted. ** = Omitted item due to low inter-total correlation.* *Continued on next page.*

| Construct | Items | Cronbach's Alpha | Item-Total Correlation | Original items | Retained Items |
|---|---|---|---|---|---|
| Resistance to Change (RC) | | 0.828 | | 3 | 3 |
| RC_1 | I do not want the medical apps to change the way I make decisions. | | 0.718 | | |
| RC_2 | I do not want the medical apps to change the way I interact with other people on my job. | | 0.635 | | |
| RC_3 | I am not willing to take on any risk by replacing my current work with medical apps. | | 0.71 | | |
| Security (S) | | 0.774 | | 3 | 3 |
| S_1 | I am worry about leakage of sensitive information on the use of medical apps. | | 0.542 | | |
| S_2 | Using medical apps will render me to cyber security risks. | | 0.712 | | |
| S_3 | I do not feel secured using medical apps in my work. | | 0.596 | | |
| Device/Apps Compatibility (DAC) | | 0.573 (.935)* | | 3 | 2 |
| DAC_1** | I am not comfortable with the use of mobile technology and its related product. | | -0.008 | | |
| DAC_2 | Medical apps are compatible with the work I generally work. | | 0.708 | | |
| DAC_3 | Medical apps are compatible with other system I use. | | 0.601 | | |

*Table 2: Cronbach's alpha and item analysis of measurement items in pilot testing. * = Cronbach's alpha value after item was omitted. ** = Omitted item due to low inter-total correlation.*

| Path | Hypothesized Effect | Path Coefficient | Observed t-value | Sign |
|---|---|---|---|---|
| H1: PU → BI | + | 0.4382 | 7.0613 | *** |
| H2: PEOU → BI | + | 0.1795 | 3.2201 | ** |
| H3: SN → PU | + | 0.1652 | 2.5285 | ** |
| H4: RD → PU | + | 0.4128 | 7.414 | *** |
| H5: RD → PEOU | + | 0.3472 | 4.9724 | *** |
| H6: DAC → PU | + | 0.27 | 3.3802 | *** |
| H7: FC → PEOU | + | 0.1254 | 3.4017 | *** |
| H8: RC → BI | + | 0.069 | 1.7329 | > 0.05 |
| H9: RC → PU | - | -0.2514 | 3.6889 | *** |
| H10: RC → PEOU | - | -0.1125 | 2.1911 | * |
| H11: S → RC | + | 0.3978 | 8.8095 | *** |

* p< 0.05 ** p < 0.01 *** p < 0.001 (based on t(414), two tailed test)

*Table 3: Path Coefficient Analysis using SmartPLS*

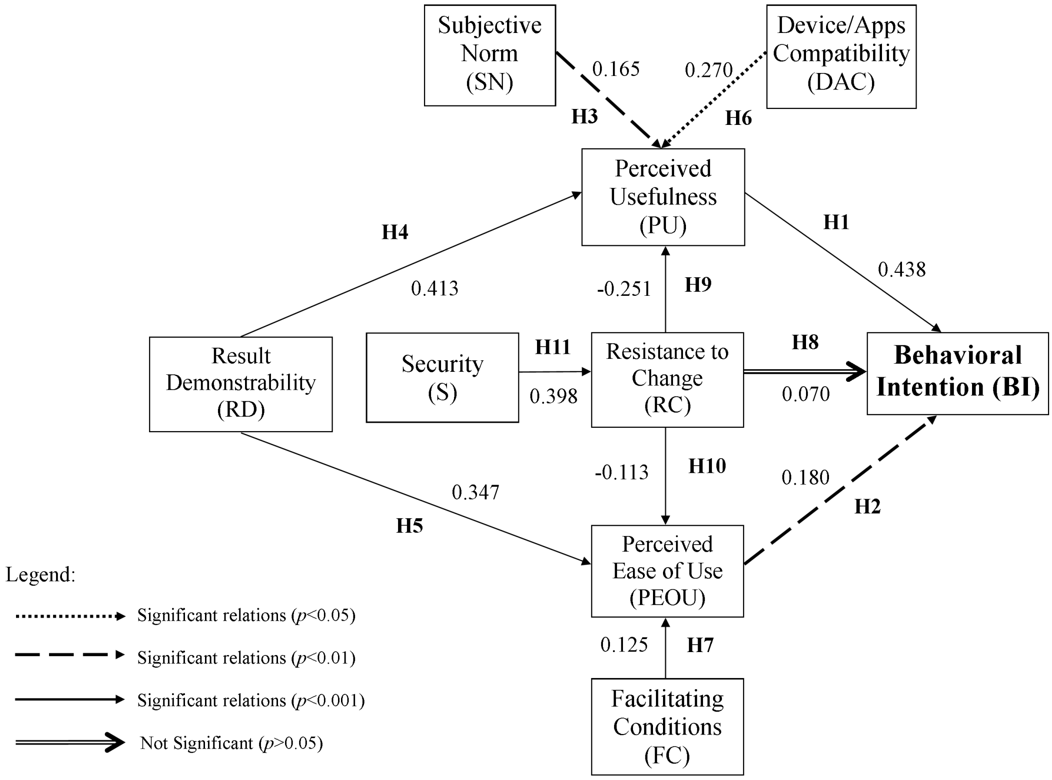


*Figure 2: Statistical significance of path coefficients*

| Construct | Cv-communality H2 | Cv-redundancy F2 |
|---|---|---|
| Behavioural Intention (BI) | | 0.2602 |
| Perceived Ease of Use (PEOU) | 0.3128 | 0.0963 |
| Perceived Usefulness (PU) | 0.4723 | 0.2243 |
| Resistance to Change(RC) | 0.3272 | 0.0928 |
| Device/Apps Compatibility (DAC) | 0.3426 | |
| Facilitating Condition (FC) | 0.3363 | |
| Result Demonstrability (RD) | 0.3442 | |
| Security (S) | 0.5739 | |
| Subjective Norm (SN) | 0.375 | |

*Table 4: Results of cv-communality (H2) and cv-redundancy (F2)*

inexpensive solutions to training and professional development. This study showed that pharmacists accepted the use of medical apps only when it was demonstrating reliable and desired utility in their practices.

The study has also confirmed that the effect of perceived usefulness of medical apps by pharmacists is mediated by three positive relationship factors, i.e. result demonstrability, subjective norm and device/apps compatibility issues. Most prominently being the result demonstrability that possessed the strongest influence on how pharmacists perceive the usefulness of the apps. This is because despite of all the advocated advantages of medical apps that could possibly bring forward for a change in pharmaceutical care, pharmacists are cautiously approving these apps unless the tangibility of the outcomes is convincible. Reliability, accuracy and evidence-based of the information provided by medical apps such as drug reference and treatment guidelines apps are deemed to be pivotal in everyday of pharmacy practice. Comparatively, subjective norm and device/apps compatibility issues contribute to a lesser extent on perceived usefulness. Apparently, autonomous practice in pharmacy profession requires pharmacists to make independent judgement and decision, subsequently placing less weight on others' opinions. Therefore, subjective norm has a little effect on their perception about medical apps. Similarly, compatibility issues of device and apps have only minimal effect on perceived usefulness mostly due to the robust development of sophisticated mobile technology in recent decades. Most of the mobile devices today, be it smartphones, tablets or phablets from various brands and models, are powerful and capable enough of running all types of medical apps available on the market.

Resistance to change were the only negative determinant of perceived usefulness. In other words, when intrinsic behavioural resistance was present in someone's mind-set, perceived usefulness of the system would be reduced due to aversion towards innovations. Resistance to change was also referred to as social inertia that served as a cognitive force to preserve status quo and preclude change in an organisation [74]. In this study, pharmacists perceived that a sudden change in their workflow as a threat because of fear of losing control over their familiar work. Other potential lost imposed by the use of medical apps included loss of organizational status and power, and loss of control over organizational resources. The results showed that negative feelings still beheld in pharmacists' attitude in acceptance of medical apps because changes were often disconcerting and inevitably associated with insecurity.

### 4.2 Perceived Ease of Use

In this study, perceived ease of use had shown a direct positive effect towards behavioural intention. Perceived ease of use was a relatively weaker determinant of intention to use medical apps compared to perceived ease of use. Due to the nature of work in pharmacy fields, pharmacists seemed to have good mental and cognitive capacity and high adaptability to new technologies that they did not seem to consider ease of use an issue of particular important. This is true because medical apps are generally simpler in design and were user-friendly. Nevertheless, other factors such as age should be further considered because older generation of pharmacist were generally regarded as less technology-savvy compared to the younger generation of pharmacists. Hence, it is preferable that implementation of new medical apps to be initiated first within younger pharmacists to minimise setbacks for its adoption.

Interestingly, the effect of perceived ease of use was determined by two direct positive factors: result demonstrability and facilitating conditions. Similar to perceived usefulness, medical apps were perceived to be effortless to use if the system was able to prove its relevance to pharmacist's daily job tasks. This was due to the reason that minimum time spent on adapting to new apps could be compensated by improved job performances and efficiency in long run. Besides, key facilitating conditions such as availability of training and technical assistance, financial reimbursements by employer and seemingly high speed wireless connection were deemed to be crucial to ease the use of medical apps on mobile devices, which in turn would facilitate the acceptance of this technology by pharmacists. It is therefore important for higher management personnel to look into these elements if they are to facilitate full adoption of any new HIT within the institutions.

On the other hand, resistance to change seemed to have a direct negative effect on perceived ease of use. Intrinsically and subjectively, pharmacists might refuse to change and opt for maintaining status quo, reverting to the original states despite of all the advocated benefits of such system. Prejudicially, pharmacists' perception on how easy to use medical apps in their work would drop dramatically due to the fear of change. Ultimately, this will lead to lack of innovation diffusion for the reason that certain pharmacists are not willing to try out on the innovation due to prejudgment that the system acquires a lot of effort to use.

### 4.3 Resistance to Change

Resistance to change was proposed as one of the key negative factors that served as an inhibitor to the be-

| Construct | $R^2$ | Communality | $H^2$ | Redundancy | $F^2$ |
|---|---|---|---|---|---|
| Behavioural Intention (BI) | 0.28 | 1 | | 0.099 | 0.2602 |
| Perceived Ease of Use (PEOU) | 0.182 | 0.657 | 0.3128 | 0.019 | 0.0963 |
| Perceived Usefulness (PU) | 0.318 | 0.746 | 0.4723 | 0.048 | 0.2243 |
| Resistance to Change(RC) | 0.158 | 0.659 | 0.3272 | 0.1 | 0.0928 |
| Device/Apps Compatibility (DAC) | | 0.794 | 0.3426 | | |
| Facilitating Condition (FC) | | 0.637 | 0.3363 | | |
| Result Demonstrability (RD) | | 0.673 | 0.3442 | | |
| Security (S) | | 0.801 | 0.5739 | | |
| Subjective Norm (SN) | | 0.809 | 0.375 | | |
| Average | 0.235 | 0.753 | | | |
| GoF = $\sqrt{}$ (average R2*average communality) = $\sqrt{0.176545}$= **0.4202** | | | | | |
| Note: H2 = cv-communality index, F2 = cv-Redundancy index | | | | | |

*Table 5: Communality, redundancy and GoF.*

havioural intention. Contrary to the previous study conducted on physicians' resistance towards HIT by Bhattacherjee and Hikmet (2007), the result was not significant in this study. Interestingly, the effect of resistance to change on intention to use medical apps was mediated through both perceived usefulness (H5 & H1) and perceived ease of use (H6 & H2). In other words, perceived usefulness and perceived ease of use acted as the mediator for resistance to change. Conceivably, medical apps were too useful for pharmacists in terms of productivity that they were still willing to adopt medical apps in their daily practice even though they might be risking some minor changes in their workflow, which could be easily adjusted over short period. It was postulated that pharmacists were likely to compromise and to adopt medical apps if its use was mandatory within the given health institution. Nonetheless, the indirect effect of resistance to change on behavioural intention should not be overlooked after all.

### 4.4 Security

Security appeared to be a relatively newer behavioural intention inhibitor that has not yet been fully understood. In this study, the meaning of security was more confined to data security related to sensitive patient information such as medical, financial, family and social histories. The results of this study showed that security acted indirectly as a potent inhibitor of intention to use medical apps where its effect was mediated through resistance to change.

Pharmacists were well informed that any information transmitted via an app might be relayed to the third-party developers as well as unidentified marketers and advertisers[60]. This could render pharmacists to higher legal liability when the data that streamed through unregulated network were actually involving patient related sensitive information in which patients' privacy and confidentiality were positioned at tipping point. Subsequently, fear of improper and unethical practice because of using mobile technology such as online fraud, malicious destruction, pirating and hacking could have resulted in some pharmacists to reject the use of medical apps in their practices. Other mobile technology related security issues such as credential verification and identity theft had also become one of the major hindrances of full adoption of any HIT including mobile medical apps. Technical support from the apps developers in terms of security patches, antivirus, firewall, and data encryption must be readily available for end users to obtain ideal security protection. Essentially, patients and health care providers should be educated about the security risks involved with the use of these apps. It is not until more secured networking systems and medical apps are developed in the future that far-reaching adoption of HIT by end users was achievable.

## 5 Conclusion

To summarize, this study employed partial least square (PLS) analysis of questionnaire survey data to measure the strength of relationships between the effect of key constructs and intention to use medical apps. Eleven hypothetical situations were proposed in this study. Results of the analysis supported the theoretical model with ten proposed hypotheses were substantiated. While perceived usefulness and result demonstrability serve as critical factors in explaining pharmacists' intention to use medical apps, it is vital to pay attention to the security and privacy matters related to the use of these apps. While the resistance to change did not contribute directly to adoption of medical apps, perceived ease of use, subjective norm, device/apps compatibility and facilitating conditions therefore remain fundamental enablers and future challenges of medical apps adoption by pharmacists.

Currently there is a lack of medical apps regulations to safe guard the validity and reliability of the apps contents that are used by health care providers in their decision making processes and indirectly affecting the overall health care quality. It is believed that initiatives of self-regulation processes will be instigated in the very near future to ensure that medical apps used by health care professionals are peer-reviewed, evidence-based and provide-up-to-date clinical information. In short, pharmacy is one of the crucial health care professions that must adopt informatics to embrace benefits delivered by technologies in improving health care quality.

The development of technology is never slowing down. It will continue to advance and to change every facet of our daily lives. Many new aspects of health information technology such as cloud computing, remote health monitoring and telehealth are enriching the complexity of health care game. Technology acceptance study will remain an important topic of research because mobile health is not about the technology but it is about the behaviour change. This is particularly true because implementation of health information technology has been proven to be challenging for many institutions and business with minimum adoption by patients, caregivers, providers and payers.

## Conflicts of Interest

None.

## Appendix – Sample Questionnaire

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