McMaster eBusiness Research Centre

The Role of Support and Sustainability Elements in the Adoption of an Online Self-Management Support System for Chronic Illnesses

By

Reza Aria and Norm Archer

McMaster eBusiness Research Centre (MeRC)

WORKING PAPER No. 58
June 2016

McMaster University

THE ROLE OF SUPPORT AND SUSTAINABILITY ELEMENTS IN THE ADOPTION OF AN ONLINE SELF-MANAGEMENT SUPPORT SYSTEM FOR CHRONIC ILLNESSES

By

Reza Aria and Norm Archer

MeRC Working Paper # 58
June 2016

DeGroote School of Business
McMaster University
Hamilton, Ontario, L8S 4M4
Canada

archer@mcmaster.ca
aria@ryerson.ca

ABSTRACT

The cost of treating chronic disease in Canada has risen to an average of 45%. Thus, more attention is being directed to health and disease self-management, to help patients mitigate and manage their chronic diseases. This study investigates how decision support, education and training and a rewards system, help and motivate patients to adopt the proposed system. The proposed model was tested by using data collected from a survey including 198 participants. The study reveals that: individuals' perceptions on performance and effort expectancy, and hedonic motivation were influenced by the proposed elements; further, age has an influence on behavioral intention.

Keywords — mobile health, e-health, self-management, decision support, chronic disease

INTRODUCTION

Mobile health has become a new trend of applications and research in healthcare due to the recent boom of information and communication technologies. The abundance and availability of many new technologies such as tablets, smartphones and other communication technologies and their ability to support the collection of patient health data, the delivery of such information to clinicians, and the real-time monitoring of patient health status has attracted the interest of clinicians and developers alike [1]. Further, there are indications that active patient involvement in disease self-management improves patient outcomes. For example, a systematic review [2] of the effectiveness of online patient self-management programs in eleven randomized controlled trials (RCTs) found that online systems were effective when compared to no intervention, and incorporating behaviour change techniques was more effective than interventions that did not. A self-management [3] program in South Australia (based on the Stanford Chronic Disease Self-Management Program or CDSMP) evaluated the effectiveness of an online disease self-management program for arthritis, mental health condition, Type 2 diabetes, asthma, and heart disease. Data common to all chronic illnesses were collected for eight health status measures, seven behaviours, and four utilization measures. At 12 months for the 194 participants, five health status indicators, six health behaviours, and visits to emergency departments had improved significantly. A systematic review of telemedicine interventions for disease self-management [4] included several technological clinical applications. In 19 RCTs for congestive heart failure (CHF) [4], 21 for stroke, and 17 for chronic obstructive pulmonary disease (COPD), there were significant reductions in hospital admissions/ re-admissions, length of hospital stay, emergency department visits, and mortality in most studies. Cost reductions were also observed in most cases.

Based on the above and other studies, shifting more care responsibility to the patients, themselves, has become a major consideration in controlling healthcare costs. To improve the quality of care for patients with chronic illnesses, many healthcare systems have adopted the heuristic Chronic Care Model (CCM) [5]. The CCM helps patients to understand and deal with the complex nature of chronic illnesses in multiple settings. It is comprised of three different realms: the community, the healthcare system, and the provider organization [5]. According to Estes:

"*The community encompasses the wealth of resources and policies to implement healthcare. The healthcare system is founded within the context of the payment structure to reimburse for healthcare. The provider organization provides the context of the delivery system to supply healthcare. The three realms provide a general structure to understand the embedded elements of managing chronic illness*" [5] page 164.

The provider organization realm, which is the target of this study, consists of four essential elements [6]:

A. Self-management support: This prepares the patients to play a collaborative and active role in their own care processes, by helping them to understand the importance of their role;
B. Delivery system design: ensures follow-up and continuity in changes to meet patient needs by composition and proper functioning of appointment systems, practice teams, and their approaches;
C. Decision support: ensures that caregivers and patients have ready access to preventive knowledge and clinical information;
D. Clinical information: ensures that care providers can readily access patient health status information [7].

Among these elements, self-management support empowers patients and families to manage chronic illness through a collaborative care approach, where the patient becomes the principal caregiver and receives support from the patient's family and the healthcare provider organization [6].

Decision support can play a role in today's healthcare system [8]. A strong and direct relationship exists between a person's current health status and the person's awareness, health literacy, and most importantly, the decisions related to health that are made on a daily basis [9]. This helps to reduce the reliance on the person's family doctor, avoiding delays between making an office appointment and visiting the doctor to get the doctor's advice [10]. Decisions are based on the person's awareness of potential complications, supporting better health-wise decisions [9]. This is even more important for patients with chronic diseases [11]. For example, patients suffering from chronic kidney disease who are more educated and aware of their status and how to manage their disease, will make better decisions (e.g. minor adjustments to medication levels) and be better able to deal with their conditions [12].

The primary objective of this study is to contribute to the information systems (IS) and healthcare literature by shedding light on the factors which directly or indirectly influence an individual's intention to use a comprehensive health self-management support system (CHSMSS). This addresses the issues of self-management of chronic illnesses and the empowerment of patients to deal with their own healthcare conditions in collaboration with their healthcare providers. The following provides a brief description of self-management, its components, issues and barriers. Then the results of a statistical study of the perceptions of 198 people with serious chronic illnesses about the potential use of an online disease self-management system are presented.

PATIENT HEALTH SELF-MANAGEMENT

Patient health self-management, a complex and cognitive task, includes recognition and evaluation of the importance/significance of changes in conditions/symptoms, as well as the implementation of any required adjustments to treatment [13]. The self-management process is highly dependent on patient judgment and decision-making ability. Access to healthcare professionals, relevant education, and training are needed to build the required skill set for patients for self-management [14].

Self-management has four internal components [15]: 1) Self-monitoring, 2) Self-care, 3) Adherence, and 4) Decision Support. Further, there are two external components that can help patients in a supportive and sustainable manner, including:, 1) Education and training [9], and 2) Sustainability elements [16] including a patient reward system.

A. Internal Components

1) Self-monitoring

Self-monitoring is defined as "the continuous and ongoing assessment and monitoring of the symptoms of a certain health condition (problem or disease), as well as other important factors (such as weight, sleep, etc.) at any place other than a clinic (e.g., home, workplace, etc.) by patients or their care partners (possibly a family member)" [17].

2) Self-care

Self-care is defined [18] as "a naturalistic decision-making process that patients use in the choice of behaviors that maintain physiological stability (symptom monitoring and treatment adherence) and the response to symptoms when they occur." Self-care includes the following inter-related behaviors: exercise and weight loss, preventive behavior such as body and oral hygiene, etc., dietary adherence, symptom monitoring, complying with prescribed medication and non-prescribed (e.g. herbal) remedies, smoking cessation and alcohol restriction.

3) Adherence

Adherence is defined as "a specific behavior of patients who accept and follow special treatment regimens prescribed by their physicians" [19]. The level of adherence for most chronic illnesses tends to drop from the time when an initial regimen is prescribed [19]. Moreover, about half of all patients don't continue with their prescribed regimens beyond a year [20].

4) Decision support

Patients may be supported through the health self-management process by a decision support system (DSS). The DSS assists patients in their decision-making activities by compiling useful information based on treatment guidelines, raw data, acceptable ranges for patient vital signs (blood sugar, heart rate, blood pressure, etc.) and other status indicators (body weight, etc.) [21].

B. External Components

1) Education & Training

Education and training have a significant positive influence on a person's ongoing and related decision-making and well as his/her current health status and awareness and health literacy [9], [22], especially in cases of chronic disease [12].

2) Sustainability Elements

Sustainability, as defined by Loman et al. (2010) is: "the continued implementation of a practice at a level of fidelity that continues to produce intended benefits," thereby becoming a desired goal for successful interventions. Unfortunately, the growing burden of chronic illnesses threatens the

sustainability of healthcare systems everywhere. Therefore, a new approach is needed to improve the continuous delivery of primary care services for chronic diseases and ensure the sustainability of care [23].
According to several studies [24], [25], [26] rewards and incentives provide a strong motivation for behavior change. Therefore, a type of reward mechanism can be incorporated into a disease self-management system in order to motivate change and to discourage patients from abandoning the system. Patients will collect points by regularly using such a reward mechanism; these points can be converted into gift cards, movie theatre tickets, etc. when a certain limit is reached.

IMPORTANCE OF CONTEXTUALIZATION

In developing a new theory, generalizability to different settings is important for both research and practice [27]. Generally, parsimonious theories which provide reasonable levels of predictive and explanatory power are favoured [28]. However, the need for more practical relevance and richness in information systems (IS) research has been the reason for more contextualization of the theories in this field [27].

According to [29] Page 386, context is defined as "*situational opportunities and constraints that affect the occurrence and meaning of organizational behaviour as well as functional relationships between variables*". Although a variety of contextual features such as user characteristics, task types, technology characteristics, and organizational factors has been examined by different studies, most of them were studied in isolation and not collectively. Hence there is a need for a more systematic approach for contextualization in IS research [27].

In this research, in order to contextualize the chosen adoption model to the specific research context, the relevant core constructs of the model need to be captured and more exploration is needed on the assumptions and boundaries of the model by adding more relevant context-specific constructs to the model [27]. Hong et al. (2014) have suggested the following guidelines in order to contextualize a chosen model to the specific context of the research:

a) The research should be grounded in a general theory (model)
b) The grounded theory should be contextualized and refined to be suitable for the context of the research
c) The theory should be thoroughly evaluated to identify the context-specific factors
d) Any identified context specific factors should be modelled
e) The interplay between technology artefact and other factors should be examined
f) Other alternative context-specific models should be considered.

BACKGROUND THEORY & CONTEXTUALIZATION

The *Technology Acceptance Model* (TAM) [30] is a well-known theory that models how users come to accept a new technology. TAM suggests that when users are presented with a new technology, the user's perceived view of that technology (i.e. perceived ease of use and perceived usefulness) is an essential determinant to user acceptance. According to Davis et al. (1989), perceived usefulness (PU) is "the degree to which a person believes that using a particular system would enhance his or her job performance", and perceived ease-of-use (PEoU) is "the degree to which a person believes that using a particular system would be free from effort".

During the past decades, TAM has been used, and expanded in order to explain the behavioural intension of users for adoption and use of many new technologies. Moreover, many modified versions of TAM have been developed, including TAM 2 [31], the *Unified Theory of Acceptance and Use of Technology* or UTAUT [32] and TAM 3 [33] for similar purposes. Each of these models proves the effectiveness of the two major determinants Perceived Ease of Use (PEoU) and Perceived Usefulness (PU) (equivalent to effort expectancy and performance expectancy respectively in UTAUT [33]) in the acceptance and usage prediction of a new technology. In UTAUT, facilitating conditions and social influence are two influential factors that could potentially affect the adoption and use of a new technology where age, gender and experience of the users are moderators for the impacts of these influential factors [32]. These theories are suitable for use in predicting the adoption of a new system. In this research we therefore chose the one which is the most relevant to this context.

Following the first two guidelines of Hong et al. (2014), UTAUT2 was chosen to guide the development of a context-specific model for this research. After a longitudinal study of the various factors and variables that influence user adoption and use of a new technology, Venkatesh et al. [34] introduced the second version of the *Unified Theory of Acceptance and Use of Technology* (UTAUT2) by adding three important constructs (hedonic motivation, price value and habit) to the original UTAUT constructs (performance expectancy, effort expectancy, social influence and facilitating conditions). UTAUT2 also inherited all three moderator variables (age, gender and experience) from the original UTAUT model.
Venkatesh et al. (2012) Page 161, defined hedonic motivation as "*the fun or pleasure derived from using a technology",* which has been shown to play an important role in determining technology acceptance and use [34]. Research has found that such hedonic motivation directly influences technology acceptance and use and is an important determinant in this context. Therefore, it is important that hedonic motivation be considered in this research as a predictor of user intention to use the proposed CHSMSS.

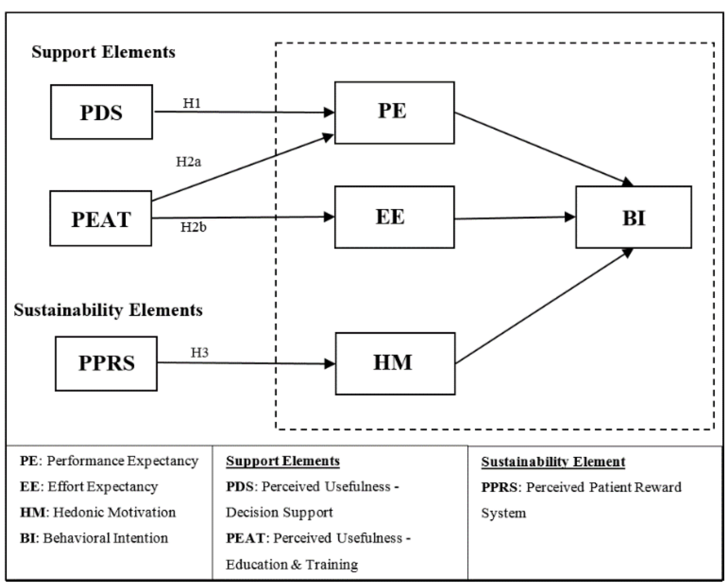

Figure 1. Simplified CHSMSS Model

Table 1. Construct Definition

Construct	Definition
Perceived Usefulness - Decision Support	How useful would patients perceive the Decision Support element to be in their health-related daily decision making process. Adapted with minor changes from [35].
Perceived Usefulness - Education & Training	How useful would patients perceive the Education and Training element to be useful in their daily process of health self-management? Adapted with minor changes from [35].
Perceived Patient Reward System	How the reward element would affect the patients perception on using the proposed CHSMSS. Adapted with minor changes from [34].
Performance Expectancy	The degree to which a patient believes that using the proposed CHSMSS will help him or her to attain gains in health status. Adapted with minor changes from [34].
Effort Expectancy	The degree of ease or effortlessness associated with the use of the proposed CHSMSS. Adapted with minor changes from [34].
Hedonic Motivation	The perceived fun, pleasure or interest derived from using the proposed CHSMSS. Adapted with minor changes from [34].
Behavioral Intention	The perceived likelihood or subjective probability that patients will engage in using the proposed CHSMSS. Adapted with minor changes from [34].

The UTAUT2 model has been tested through a longitudinal empirical study and has been proven to be a robust predictor of information system adoption as well as usage continuance behavior [34]. UTAUT and its related predecessors (TAM, etc.) have been applied in a large number of technologies in various settings with successful results [34]. Therefore UTAUT2 was chosen to be the base research model for this study.

However, UTAUT2 has other constructs such as Price Value and Facilitating Conditions, Social influence and Habit. Price Value and Facilitating Conditions are not relevant here since they won't be affected, at least not in Canada, since such a system would likely be provided at public cost for everyone. Further, Social Influence and Habit won't be affected since the proposed CHSMSS had not been offered to study participants to use, so they would have no prior experience with the system. Therefore, the model was simplified to contextualize and tailor it towards the purpose of this research [27] by eliminating Social Influence, Facilitating Conditions, Price Value and Habit constructs. The simplified model is demonstrated in Figure 1. Table 1 shows the definition for each construct in the model.

It is not exactly clear what influences user beliefs in the UTAUT model [34], [36]. Brown et al. (2010) have shown that the UTAUT model as a whole could be a mediator between user beliefs and actual use behaviour. They developed a framework that relates some constructs that are believed to influence these beliefs as antecedents of the key constructs (Performance Expectancy, Effort Expectancy, etc.) of the model. In line with this approach and following the third guideline by Hong et al. (2014), we explore what would influence the user's beliefs to adopt and use CHSMSS. In this research, we argue that user beliefs about CHSMSS are influenced by a set of facilitators provided by the system. These facilitators are divided into two broad categories: Support Elements and Sustainability Elements. The first category, "Support Elements", includes care provider support [37], decision support [21], family and community support [38], and education and training [9], [12]. All of these major factors influence the performance expectancy of the system in some way. They also affect user satisfaction with the system indirectly. Therefore all are included in our proposed research model. The second category, "Sustainability Elements", includes a patient reward system [14]. These factors affect the hedonic motivation of users to adopt and to continue using CHSMSS.

Following the fourth and fifth guidelines by Hong et al. (2014), the direct effect of the support and sustainability factors and the addition of relevant constructs to the theoretical framework are proposed. Thus, there is an opportunity to test a full model along with those facilitators that are believed to influence user beliefs (performance expectancy, effort expectancy) as well as their hedonic motivation. Finally, following the sixth guideline of Hong et al. (2014), statistical saturation analysis can be performed to test for the presence of any other alternative relationships.

HYPOTHESES AND THEORY DEVELOPMENT

A. Support Elements

As demonstrated in Figure 1, there are two support elements: perceived decision support and perceived education & training.

1) Perceived Usefulness of Decision Support (PDS)

The degree of deployment of decision support tools is one of the measures of support in decision making [39]. As discussed earlier, decision support element is an important factor in patient health self-management. However, the hypotheses that are tested here relate to the impact of the decision support element on the performance expectancy of the system. Interpretability and transparency are two desirable features of a DSS. Research has shown that acceptance of a DSS is closely related to the usefulness of recommendations made by the system. In the case of medical decision support, where the decisions may have serious impacts and consequences on the user's health, it is crucial that users have transparency and interpretability in the decision support that they receive. More transparent and interpretable recommendations improve the usefulness of the system considerably and in turn the system becomes more acceptable by the users [40].

Therefore, it is hypothesized that:
H1: *Perceived usefulness of decision support has a positive influence on user perceptions of the performance expectancy of the CHSMSS.*

2) Perceived Education and Training (PEAT)

Bandura's social cognitive theory [41], distinguishes two types of experiential learning conditions: enactive mastery (EM) and vicarious experience (VE). The former refers to "actively performing a specific task during experiential training" while the latter refers to "viewing another person actively performing the task". According to [42] experience can have a substantial impact on the perceptions of users about the necessary effort that should be expended in order to learn and use a product. Luse et al. (2013) explain that effort expectancy in the UTAUT model is built upon social cognitive theory [41] and is related to efficacy beliefs and influences the determination of an outcome expectancy. They also explain that individual motivation as well as expectation from a new technology differ, based on the effect of the training context as well as greater influencing perceptions and behaviour related to the training environment, which leads to beneficial outcomes such as system adoption and use behaviour. Performance expectancy is determined by a match between the person's needs and the technology's capabilities [42], since it is an outcome belief [43]. Therefore, educating users about what to expect from the system would directly influence their outcome beliefs regarding performance expectancy of the CHSMSS. Therefore, it is hypothesized that:

H2a: *Perceived usefulness of education and training has a positive influence on user perceptions of the performance expectancy of the CHSMSS*.

According to the *Extended Theory of Planned Behavior* [44], behavioural intention is the most influential factor in predicting actual behaviour, and *Perceived Behavioral Control* (PBC) has a direct influence on behavioural intention. Perceived behavioural control is a "*set of control beliefs and their perceived power to facilitate or inhibit the performance of a behaviour*" [44] Page 117, and is defined as "*person's perception of how easy or difficult it would be to carry out a behaviour*" [44] Page 119, which is similar to *Effort Expectancy* (EE) in the UTAUT2 model [34]. In this case, those beliefs (EE) are directly influenced by education and training, since users learn what the components and features of the system are, where they are located, and how easy it is to use them in an effective manner. Therefore, it is hypothesized that:

H2b: *Perceived usefulness of education and training has a negative influence on user perceptions of the effort expectancy of the CHSMSS*.

B. Sustainability Elements

A sustainability element is a support offered by the system to encourage patients/users to adopt and continue using the system. Patient rewards can impact hedonic motivations of the patients to do this. Instruments to measure this construct have been developed (Venkatesh, Morris, Davis, & Davis, 2003) and [34].

Perceived Patient Reward System (PPRS)

Hedonic motivation is defined as "*the fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use*" [34], page 161. According to different studies [24], [25], [26] rewards and incentives provide a strong motivation for behaviour change. Further, Garavan et al. studied the neurobiology of reward processes and cognitive control that resulted in an effective role of the reward in behaviour change for the treatment of addiction [26]. Their results confirm the effectiveness of rewards in successful recovery from addiction. In another study [25], the relationships between a more specific type of reward, financial incentives, and performance of crowds in two different experiments were investigated. Their results confirm that presence of such incentives affects the behaviour of participants and also increases financial incentives, increasing the quantity of work performed by participants. Thus, it seems very beneficial to have a reward system implemented in CHSMSS. Therefore:

H3: *Patient perceptions of rewards and incentives offered for using the CHSMSS have a positive influence on user hedonic motivation to adopt and use it*.

The relations between Performance Expectancy (PE), Effort Expectancy (EE) and Hedonic Motivation (HM) with Behavioural Intention (BI) were not hypothesized, since the model was based on UTAUT2 [34], a pre-validated model.

METHODOLOGY & RESULTS

For the purpose of this research, a group of 204 patients, who suffer from a serious chronic disease (e.g. heart failure, rheumatoid arthritis, diabetes, etc.) participated in an online study to determine whether watching a video clip about features and functionalities of a prototype CHSMSS in their home environment would be effective in motivating them to adopt the system. It was anticipated that patients with serious chronic disease would relate closely to this study since they had to deal with symptoms and effects of their illness on a routine daily basis.

A commercial provider firm (ResearchNow) provided a database of potential participants. It has a database of members (potential participants) that has been collected continuously for years. Upon enrolment, members complete an extensive membership profile survey. This identifies the specific attributes of an individual and the company continuously monitors these data points for any changes. Therefore, the company is aware of the specific chronic diseases that its members (potential participants) have, and contacted them on that basis for this specific study.

An introductory video clip about the various capabilities of CHSMSS, with a focus on support and sustainability elements, was produced and used to introduce this health self-management system to participants. The purpose was to study their perceptions of the system, and to note their decisions on how useful it might be in managing their chronic illnesses. An online cross-sectional survey method was employed to collect data and test the hypotheses postulated in the previous section. The survey questionnaire and methodology was approved by a university Research Ethics Board. Administering a survey after participants had watched the video in order to test the proposed research model was appropriate, since surveys are accepted as one of the most effective tools in information systems research [45]. Moreover, using surveys, according to Webster and Trevino [46], is a typical approach to validate adoption models.

Before starting the final online data collection procedure, a pilot study was conducted by the contractor with an initial 20 participants. The results were analyzed carefully to determine whether any changes to either the online survey or the data collection procedure were needed. None were found, so the full survey was completed. Data from the pilot study were therefore included in the final dataset for analysis.

We screened potential participants in our study using three mandatory questions at the beginning of the questionnaire:

- I am 18 years of age or older Yes / No
- I have been diagnosed by a physician to have a serious chronic illness Yes / No
- Chronic illnesses can rarely be cured Yes / No

A “No” answer to any of these questions would result in a message to participants that they could not continue participating since they were not eligible. Upon completion of the survey, each participant received fair market compensation based on their membership agreement with the contractor collecting the data. Due to company policy, no compensation was provided for participants who did not finish the questionnaire.

The survey stopped as soon as it reached the pre-defined limit of ~ 200 completed responses. Based on the number of predictors and the largest number of paths leading to a single variable (shown in Figure 2), a sample size of 90 or higher was suitable to check the validity and reliability of the model [47]. However, according to rules for sample size [48], a sample size of about 200 is suitable for almost all types of statistical analysis (e.g. measuring group differences, relationships, and Chi-Square, etc.). The decision to use the 200 data points ensured the validity and reliability of the study. It was decided to collect data from 100 participants from each country (Canada & US). Because data collection was stopped due to this limitation on the number of participants, response rate calculations are not relevant for this study.

The raw data consisted of an initial set of 204 completed surveys. The database was reviewed for missing data, as well as any anomalies or possible outliers. After eliminating responses containing these, the resulting final dataset included 198 valid cases (N=198). Further, there were a few cases in which data were missing. After applying Expectation-Maximization [49] to the dataset, a complete dataset ready for statistical analysis was available.

PLS-SEM (partial least squares – structural equation modelling) was used to analyze the data. PLS was chosen due to its strong capabilities in model evaluation, reporting and minimum data requirements [50]. SEM was chosen because it provides a capability for investigation and analysis of unobservable variables that are indirectly measured from observable variables, especially when the sample size is relatively small [51]. According to Chin & Newsted (1999), the PLS method should be employed to validate the research model when the theoretical model is relatively new and in early stages of development, which is the case in this study. It also gives optimum prediction accuracy because of its prediction orientation nature [52], [47], [53]. All constructs in this study including PE, EE, HM and BI as well as Support & Sustainability (PDS, PEAT, PPRS, POSN and PETC) were modelled as reflective constructs in the research model [47]. Table 1 demonstrates the reflective constructs used, all adapted from pre-validated constructs from previously published works.

A. Measurement Model Evaluation

1) Individual Item Reliability Tests

Model evaluation started by assessing individual item reliability with the following specified criteria. The results are shown in Table 2.

Table 2. Results of Individual Item Reliability Assessment

Construct	Item	Item Loading	Corrected Item-Total Correlation
BI	BI-1	0.993	0.881
	BI-2	0.992	0.869
HM	HM-1	0.933	0.842
	HM-2	0.971	0.797
	HM-3	0.942	0.861
PE	PE-1	0.991	0.870
	PE-2	0.992	0.889
EE	EE-1	0.968	0.882

	EE-2	0.962	0.870
PDS	PDS-1	0.945	0.816
	PDS-2	0.965	0.824
	PDS-3	0.966	0.824
PEAT	PEAT-1	0.976	0.823
	PEAT-2	0.972	0.785
PPRS	PPRS-1	0.994	0.863
	PPRS-2	0.994	0.865

- *Corrected Item-Total Correlation*: This is the coefficient of the correlation between the item and a total score for the remaining items of the construct to which the item belongs [54]. Although there is no specific criterion, a rule of thumb suggests that any items with correlation values below 0.4 need to be eliminated before any analysis on the factors [55], [56], [57]. The value of 0.5 was chosen as a more conservative criterion which should lead to more robust results from PLS analysis.
- *Item Loading*: Most of the related references suggest removing very weak indicators and keeping the items with loadings above 0.5 [58], [59].

2) Construct Reliability Tests

The reliability of the constructs was also assessed using the following criteria. The results are shown in Table 3.

- *Cronbach's Alpha (α):* This is a measure of internal consistency of a construct [60]. Although the measure of 0.7 is considered the minimum required for internal consistency, values equal to or above 0.8 are often considered to be the minimum [61].
- *Composite Reliability (CR):* CR is a measure of internal consistency and reliability of a construct when it is combined with other constructs in the model [62]. Although 0.7 is considered the minimum required for internal consistency and reliability, values equal to or above 0.8 are often considered to be the minimum [61].
- *Average Variance Extracted (AVE):* This is the amount of variance captured by the construct, in relation to the amount of variance due to measurement error, and values greater than **0.5** are considered to be acceptable [63].
-

Table 3. Results of Construct Reliability Assessment

Construct	AVE	Composite Reliability (CR)	Cronbach's Alpha
BI: Behavioural Intention	0.985	0.993	0.985
EE: Effort Expectancy	0.931	0.964	0.926
HM: Hedonic Motivation	0.900	0.964	0.945
PDS: Perceived Decision Support	0.919	0.972	0.956
PE: Performance Expectancy	0.983	0.991	0.983
PEAT: Perceived Ed. & Training	0.949	0.974	0.947
PPRS: Perceived Patient Reward System	0.987	0.994	0.987

3) Validity Assessment

In order to test the validity of the model and its constructs, a confirmatory factor analysis (CFA) was performed in order to generate a matrix of loadings and cross loadings. Then loadings and cross-loading were populated and used to form a matrix (Table 4) to evaluate the validity of the measurement model. According to the Geffen and Straub (2005) guideline, a measurement item should load on its latent construct at least one order of magnitude more than its loading on any other latent construct(s). Finally, items in the matrix were carefully examined and confirmed to load on their corresponding constructs stronger than other constructs as per the guideline provided by Geffen & Straub (2005).

Furthermore, a discriminant validity test was performed to ensure that constructs in the model are different from each other. According to [64], discriminant validity exists when the correlations between items in any two constructs are lower than the square root of the AVE (average variance extracted) shared by items within a construct. Table 5 demonstrates the construct correlation matrix for the model. In Table 5, the square roots of the AVEs (diagonal elements) do not exceed the inter-construct correlations below and across from them. Thus adequate discriminant validity exists.

Table 4. Matrix of Loadings and Cross-Loadings

Item	Construct						
	BI	**EE**	**HM**	**PDS**	**PE**	**PEAT**	**PPRS**
BI-1	**0.992**	0.545	0.795	0.742	0.784	0.689	0.826
BI-2	**0.992**	0.538	0.793	0.728	0.767	0.675	0.817
EE-1	0.521	**0.967**	0.682	0.552	0.586	0.490	0.554
EE-2	0.533	**0.961**	0.663	0.491	0.483	0.389	0.503
HM-1	0.762	0.650	**0.933**	0.745	0.786	0.744	0.769
HM-2	0.763	0.706	**0.970**	0.688	0.715	0.691	0.736
HM-3	0.751	0.629	**0.942**	0.653	0.676	0.666	0.743
PDS-1	0.706	0.525	0.695	**0.945**	0.772	0.757	0.698
PDS-2	0.708	0.507	0.699	**0.965**	0.817	0.754	0.685
PDS-3	0.716	0.528	0.717	**0.966**	0.798	0.785	0.717
PE-1	0.770	0.526	0.748	0.818	**0.991**	0.779	0.771
PE-2	0.780	0.576	0.769	0.828	**0.991**	0.788	0.768

PEAT-1	0.681	0.483	0.735	0.804	0.789	**0.976**	0.674
PEAT-2	0.657	0.406	0.703	0.748	0.750	**0.972**	0.656
PPRS-1	0.811	0.538	0.787	0.729	0.773	0.689	**0.993**
PPRS-2	0.835	0.553	0.783	0.721	0.770	0.668	**0.993**

Table 5. Construct Correlation Matrix

Item	BI	EE	HM	PDS	PE	PEAT	PPRS
BI	**0.991**						
EE	0.546	**0.965**					
HM	0.800	0.697	**0.949**				
PDS	0.740	0.542	0.734	**0.959**			
PE	0.781	0.556	0.765	0.830	**0.991**		
PEAT	0.687	0.458	0.739	0.798	0.790	**0.974**	
PPRS	0.828	0.549	0.790	0.730	0.776	0.683	**0.993**

B. Structural Model Evaluation

R-squared (R^2) is the proportion of variance explained by the antecedents of a dependent variable [65]. It is a measure of the success for predicting the dependent variable from its independent antecedents [66]. It must be at least above 0.1 and also high enough to have explanatory power [67].

PLS Path Estimates (β): The bootstrapping technique was used to determine the significance of the coefficients, based on the precision and stability of the PLS results [66]. In bootstrapping, usually about 500 resamples with replacement are taken from the original sample to obtain 500 estimates for each parameter in the PLS model. After that, t-tests are calculated for each estimated parameter in the PLS model from these 500 estimates in order to determine the statistical significances of the parameters [66]. Figure 2 and Table 6 demonstrate the results.

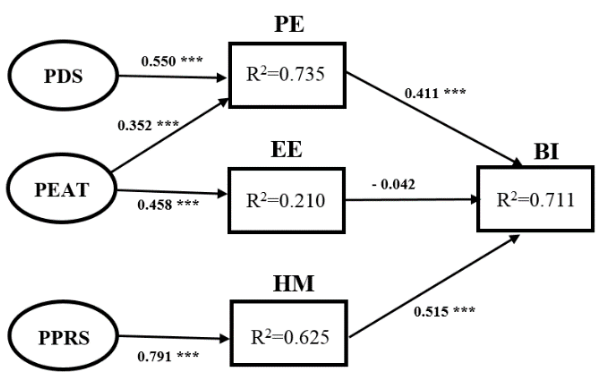

Figure 2. PLS Results for the Proposed Model

Table 6. Hypothesis Validation Results

Hypothesis	Path	Path Coefficient	t- Stat	Validation
H1	**PDS → PE**	0.550	6.024 ***	Supported
H2a	**PEAT → PE**	0.352	3.754 ***	Supported
H2b	**PEAT → EE**	0.458	5.109 ***	Supported
H3	**PPRS → HM**	0.791	5.283 ***	Supported

	PE → BI	0.411	4.788 ***	
	EE → BI	-0.042	0.515	
	HM → BI	0.515	4.538 ***	

***: p < 0.05,   **: p < 0.01,   ***: p < 0.001**

Effect Size (f^2): The effect size shows the magnitude of effect that an independent variable has over its related dependent variable. The values of effect size are viewed in four categories: between [0, 0.02), [0.02, 0.15), [0.15, 0.35), and equal to or above 0.35 The first of these categories is seen as non-significant and the rest are an indication of small, medium and large effect sizes respectively [66]. Table 7 shows the results. The effect size is calculated from the R^2 result for the dependent variable and formulated as follows:

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

Table 7. Effect size of the Independent Variables

	Dependent Variables			
Independent Variables	**PE**	**EE**	**HM**	**BI**
PDS	0.415			
PEAT	0.170	0.266		
PPRS			0.625	
PE				0.242
EE				non-sig.
HM				0.284

Cross-validated Redundancy (Q^2): This is a measure of predictive relevance of the model, or how well the model can predict the behaviour of variables [66]. A value of $Q^2<0$ is an indication of no predictive relevance and $Q^2>0$ shows predictive relevance [66]. According to Table 8, except for (EE) which has a medium predictive relevance, a large predictive relevance for all other endogenous variables is demonstrated by the model.

Table 8. Q^2 for Endogenous Variables

Endogenous Variables	**(Q^2)**
PE (Performance Expectancy)	0.717
EE (Effort Expectancy)	0.189
HM (Hedonic Motivation)	0.560
BI (Behavioural Intention)	0. 697

Goodness of Fit (GoF): Goodness of fit indicates the level of prediction performance of the PLS model on both structural and measurement levels [68]. The baseline values of 0.1(low fit), 0.25 (medium fit), and 0.36 (high fit) can be used to assess the overall fit of the model [69], [70]. The formula to calculate the GOF is:

$$GOF = \sqrt{\overline{Communality} * \overline{R^2}} = \sqrt{(0.9497) * (0.5702)} = 0.7359$$

C. Impact of Individual Characteristics and Control Variables

In order to analyze the impact of the individual characteristics of the participants, first each individual characteristic (e.g., age) was examined as well as the changes caused by them in the explained variance of every endogenous construct in the proposed model. PLS path coefficients and the impact of each individual characteristic on all constructs in the model were examined. Table 9 shows the results.

Table 9. Individual Characteristic Effects *(f^2)* on R^2

Variables	PE	EE	HM	BI
Age	0.004	**0.102**	0.004	0.000
Gender	0.000	0.007	0.000	0.004
Educational Background	0.000	0.025	0.004	0.004
Hours of Internet Use	0.004	0.004	0.004	0.000
Smartphone Access	0.000	0.014	0.004	0.012

D. Examination of Open-Ended Questions

There were three open-ended questions as well as two related categorizing questions in the survey, in order to collect insights on the mind-set of participants regarding adoption and use of the proposed system.

First Open-Ended Question

In the first categorizing question, participants were asked to say whether they were interested in using the system and if their answer was "No", they were asked to explain why. "*If no, please tell us why. This will help us improve the proposed system for you and other potential users.*" If the answer was "Yes", the first open-ended question was ignored and the participant focus was moved to the second question. A summary of the participant responses is in Table 10.

Table 10. Results from the First Open-ended Question

Type of Concern	Number of Answers	Percentage
Too much effort	49	~ 49 %
Lack of need	22	~ 22 %
Security & Privacy	20	~ 20 %
Other concerns	10	~ 10 %

Second Open-Ended Question

The second open-ended question asked participants to provide suggestions for improving the system: *"Do you have any suggestions for making the proposed system more interesting, more useful, easier to understand, or easier to use?"*

Most of the participants said that they did not have any suggestions. A number provided positive feedback such as "good work…", "it's awesome…", "well designed system", "easy to understand", etc. while some others just said "No" or "N/A" . Suggestions that are worth considering are categorized and highlights are provided in Table 11.

Table 11. Highlights of Participant Suggestions for System Improvement

Suggestions
➢ Making it more automated to eliminate data entry, so less effort and time would be needed ➢ Support for more specific conditions ➢ Linking the system to the systems of official healthcare providers ➢ Adding a professional fitness trainer ➢ Patients should be able to see what others with similar condition are doing, rather than just what they choose to post online ➢ Education for the care partner too

Third Open-Ended Question

The third open-ended question and its related categorizing question attempted to understand the participant's perceived effort that would be needed to use the system and whether participants would see themselves using it on a daily basis. *"Do you think you would be able to find time to access the proposed system at least once a day on a regular basis? Yes /No",* and then "*Please explain how you might use the proposed system to help you with managing your chronic illness."*

Among the 198 valid responses, 118 participants (~ 60%) answered "Yes", 80 participants (~ 40%) answered "No" to the categorizing question. On the related open-ended question, most of the participants who had already stated that they would not use the system, didn't really make any usable comments. Some participants indicated that they would want to use the system, but didn't leave any usable comments. Other participants who stated that they were going to use the system, also left comments, mostly explaining how they would use specific modules.

CONCLUSIONS

Appropriateness of the CHSMSS model can be assessed in terms of three important parameters: R^2 [65], [67], Q^2 (predictive relevance) [66] and GOF (goodness of fit) [68]. In the case of R^2, a comprehensive study [32] examined eight theories of technology or information systems acceptance models by using partial least squares analysis, and compared them with UTAUT theory. It reported that R^2 for BI ranged from 0.30 to 0.38 for these theories, and that the R^2 for UTAUT in the pre-use stage was 0.52. Another study [34] compared differences in R^2 for BI (behavioural intention) between UTAUT ($R^2 = 0.56$) and UTAUT2 ($R^2 = 0.74$). The BI in the model of this study achieved an R^2 of 0.711, which is very good in comparison with some of the most established studies in Information Systems research.

The predictive relevance of the endogenous variables in the model are very good. PE, HM and BI have a Q^2 of 0.717, 0.560 and 0.697 respectively, which indicates quite high predictive relevance for all of them. EE's Q^2 of 0.189 indicates a medium predictive relevance which is still acceptable. Moreover, the goodness of fit is also very good (0.736), indicating that the model is an appropriate model for predicting the intentions of potential users to adopt and use the system.

Based on the findings presented in the previous section, it is surprising that even though a pre-validated model (i.e. UTAUT2 [34]) was adapted to this study, the results and findings do not align entirely with previous findings. According to a variety of different studies in the context of Information Systems Research (e.g. [71], [72], [33], [34], etc.) there should be a strong correlation between performance expectancy and behavioural intention of users (PE → BI) and also between effort expectancy of the system and behavioural intentions (EE → BI) as well as hedonic motivation and behavioural intention (HM → BI). However, while there was a significant relation between PE→ BI (β=0.411, f^2=0.242) and HM→ BI (β=0.515, f^2=0.284), there was no significant relationship between EE → BI.

It is obvious that while the PE→BI and HM→BI relationships are significant and consistent with prior IS research, the introduction of new antecedent factors has resulted in a loss of effect size of the EE variable on BI. These new factors are constructs that are more related to the context of this research [27], which appear to influence the perceptions of participants in their own way.

Since the participants were mostly well-educated, with only about 10% having a high school diploma or less education, one suggestion for the non-significant effect of EE on BI could be that participants had the required education and ability to easily understand the system and the benefits it could provide. Having said that, examination of responses to the first open-ended question as well as its categorizing question showed that about half of the respondents felt that using such a system requires too much effort (i.e. daily interaction with the system, commitment to data entry, etc.). However, even those participants who stated that they did not want to use the system due to the amount of effort needed, had a positive perspective towards the potential benefits it provides for the users. In other words, the benefits of using the system outweighs the effort needed from users. The latter result may account for the finding that EE doesn't have a significant effect on Behavioural Intentions of potential users.

Although there is no significant relationship between EE and BI, the saturated model analysis shows that there is a relatively strong relationship between EE and HM (β=0.339, f^2=0.351). This means that the easier the system is to use, the more motivation users will have to use it, which is very much in line with the results from the first and second open-ended questions.

According to the results, both PDS and PEAT have a strong and significant relationship with their relative constructs, which was expected as it aligns with previous IS research. The set of hypotheses (H1 and H2a and H2b) were theorized to examine the effect of the support construct on the previously discussed user perceptions of performance and effort expectancy of the system (CHSMSS). According to the results, both PDS → PE (β=0.550, f^2=0.415) and PEAT → PE (β=0.352, f^2=0.170) relationships are significant, which agrees with prior IS research. This indicates that the support elements have a considerable effect on the perceptions of users in the sense of performance expectancy of the system (CHSMSS).

Further, the relationship between PEAT and EE was strong with high effect size (PEAT→EE: β=0.458, f^2=0.266) and in line with prior IS research [36], [34]. After saturation analysis of the model, that relationship lost significance and PEAT showed a significant relationship with HM (PEAT→HM: β=0.321, f^2=0.243), which was very interesting and certainly needs further investigations.

The third hypothesis (H3) was theorized to examine the effect of the sustainability element (PPRS) on its relative construct (HM). Interestingly, the model shows that PPRS (Perceived Patient Reward System) has a very large effect on hedonic motivation (PPRS→HM: β=0.791, f^2=0.625) as was originally theorized and expected.

Regarding the demographics of the study and according to these results it seems that, only one moderating variable (Age), had any influence on the endogenous variables of the model. Age showed a negative effect on the Effort Expectancy variable (β= - 0.261, f^2= 0.102). The reason could be that data were collected only from participants who have at least one serious chronic disease. Generally, serious chronic disease is more likely to occur at older ages and the older generation have relatively less familiarity with, and ability to use, new technology [73].

REFERENCES

1. L. Lhotska, O. Stepankova, and M. Pechoucek, “ICT and eHealth Projects,” in *Telecom World Technical Symposium*, 2011, pp. 57–62.
2. M. S. McDermott and A. E. While, “Maximizing the healthcare environment: A systematic review exploring the potential of computer technology to promote self-management of chronic illness in healthcare settings,” *Patient Educ. Couns.*, vol. 92, pp. 13–22, 2013.
3. K. Lorig, P. L. Ritter, K. Plant, D. D. Laurent, P. Kelly, and S. Rowe, “The South Australia health chronic disease self-management Internet trial.,” *Health Educ. Behav.*, vol. 40, no. 1, pp. 67–77, Feb. 2013.
4. R. L. Bashshur, G. W. Shannon, and et al, “The empirical foundations of telemedicine interventions for chronic disease management,” *Telemed. eHealth*, vol. 20, no. 9, pp. 769–800, 2014.
5. T. S. Estes, “Moving towards effective chronic illness management: asthma as an exemplar,” *Chron. Respir. Dis.*, vol. 8, no. 3, pp. 163–170, Jan. 2011.
6. T. Bodenheimer, E. H. Wagner, and K. Grumbach, “Improving primary care for patients with chronic illness, the chronic care model, part 2,” *October*, vol. 288, no. 15, pp. 1909–1914, 2002.
7. R. E. Glasgow, C. T. Orleans, and E. H. Wagner, “Does the chronic care model serve also as a template for improving prevention?,” *Milbank Q.*, vol. 79, no. 4, pp. 579–612, Jan. 2001.
8. D. L. Hunt, R. B. Haynes, S. E. Hanna, and K. Smith, “Effects of computer-based clinical decision support systems on physician performance and patient outcomes: a systematic review,” *JAMA*, vol. 280, no. 15, pp. 1339–1346, Oct. 1998.
9. Y. Tang, S. Pang, M. Chan, G. Yeung, and V. Yeung, “Health literacy, complication awareness, and diabetic control in patients with type 2 diabetes mellitus.,” *J. Adv. Nurs.*, vol. 62, no. 1, pp. 74–83, Apr. 2008.
10. S. Mitnick, C. Leffler, and V. L. Hood, “Family caregivers, patients and physicians: Ethical guidance to optimize relationships,” *J. Gen. Intern. Med.*, vol. 25, no. 3, pp. 255–260, 2010.
11. L. Haas, M. Maryniuk, J. Beck, C. E. Cox, P. Duker, L. Edwards, E. B. Fisher, L. Hanson, D. Kent, L. Kolb, S. Mclaughlin, E. Orzeck, J. D. Piette, A. S. Rhinehart, R. Rothman, S. Sklaroff, D. Tomky, and G. Youssef, “National standards for diabetes self-management education and support,” *Diabetes Care*, vol. 36, no. SUPPL.1, pp. 1630–1637, 2013.
12. L. C. Plantinga, L. E. Boulware, J. Coresh, L. a Stevens, E. R. Miller, R. Saran, K. L. Messer, A. S. Levey, and N. R. Powe, “Patient awareness of chronic kidney disease: trends and predictors.,” *Arch. Intern. Med.*, vol. 168, no. 20, pp. 2268–2275, Nov. 2008.
13. G. L. M. MacIntyre, L. Thabane, A. Cranney, R. Cook, and A. Papaioannou, “Exercise for improving outcomes after osteoporotic vertebral fracture (Protocol),” *Statistics (Ber).*, no. 7, pp. 1–10, 2010.
14. R. Ariaeinejad and N. Archer, “Importance of Mobile Technology in Successful Adoption and Sustainability of a Chronic Disease Support System,” *Int. J. Soc. Hum. Sci. Eng.*, vol. 8, no. 4, pp. 834–839, 2014.
15. J. Pogue, L. Thabane, P. J. Devereaux, and S. Yusuf, “Testing for heterogeneity among

the components of a binary composite outcome in a clinical trial.," *BMC Med. Res. Methodol.*, vol. 10, p. 49, Jan. 2010.
16. S. L. Loman, B. J. Rodriguez, and R. H. Horner, "Sustainability of a targeted intervention package: first step to success in Oregon," *J. Emot. Behav. Disord.*, vol. 18, no. 3, pp. 178–191, Mar. 2010.
17. R. J. McManus, P. Glasziou, A. Hayen, J. Mant, P. Padfield, J. Potter, E. P. Bray, and D. Mant, "Blood pressure self monitoring: questions and answers from a national conference," *Bmj*, vol. 338, pp. 38–42, Dec. 2009.
18. B. Riegel, D. K. Moser, S. D. Anker, L. J. Appel, S. B. Dunbar, K. L. Grady, M. Z. Gurvitz, E. P. Havranek, C. S. Lee, J. Lindenfeld, P. N. Peterson, S. J. Pressler, D. D. Schocken, and D. J. Whellan, "State of the science: promoting self-care in persons with heart failure: a scientific statement from the American Heart Association," *J. Am. Heart Assoc.*, vol. 120, no. 12, pp. 1141–1163, Sep. 2009.
19. J. Sidel, K. Ryan, and J. Nemis-White, "Shaping the healthcare environment through evidence-based medicine: A case study of the ICONS project.," *Hosp. Q.*, vol. 2, no. 1, pp. 29–33, 1998.
20. C. Wahl, J. Gregoire, and K. Teo, "Concordance , compliance and adherence in health care : closing gaps and improving outcomes," *Healthc. Q.*, vol. 8, no. 1, pp. 65–70, 2005.
21. E. S. Berner, *Clinical decision support systems: theory and practice*. Springer Science + Business Media, 2007.
22. S. Levey and N. R. Powe, "Patient awareness of chronic kidney disease," *Methods*, vol. 168, no. 20, pp. 2268–2275, 2008.
23. G. M. Russell, S. Dabrouge, W. Hogg, R. Geneau, L. Muldoon, and M. Tuna, "Managing chronic disease in ontario primary care: the impact of organiza- tional factors," *Ann. Fam. Med.*, vol. 7, no. 4, pp. 309–318, 2009.
24. L. Dawkins, J. H. Powell, A. Pickering, J. Powell, and R. West, "Patterns of change in withdrawal symptoms, desire to smoke, reward motivation and response inhibition across 3 months of smoking abstinence," *Addiction*, vol. 104, no. 5, pp. 850–858, May 2009.
25. W. Mason, W. Street, and D. J. Watts, "Financial incentives and the performance of crowds," *SIGKDD Explor.*, vol. 11, no. 2, pp. 100–108, 2010.
26. H. Garavan and K. Weierstall, "The neurobiology of reward and cognitive control systems and their role in incentivizing health behavior," *Prev. Med. (Baltim).*, vol. 55, pp. 17–23, Nov. 2012.
27. W. Hong, F. K. Y. Chan, J. Y. L. Thong, L. C. Chasalow, and G. Dhillon, "A framework and guidelines for context-specific theorizing in information systems research," *Inf. Syst. Res.*, vol. 25, no. July, pp. 111–136, 2014.
28. K. Charmaz, *Constructing grounded theory*. Sage, 2014.
29. G. Johns, "The essential impact of context on organizational behavior," *Acad. Manag. Rev.*, vol. 31, no. 2, pp. 386–408, 2006.
30. F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: a comparison of two theoretical models," *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, 1989.
31. V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, Feb. 2000.
32. V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of

information technology: towards a unified theory," *Manag. Inf. Syst. Q.*, vol. 27, no. 3, pp. 425–478, 2003.

33. V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decis. Sci.*, vol. 39, no. 2, pp. 273–315, May 2008.
34. V. Venkatesh, J. Y. L. Thong, and X. Xu, "Consumer acceptance and use of information technology: extending the unified theory," *MIS Q.*, vol. 36, no. 1, pp. 157–178, 2012.
35. P. A. Pavlou, "Consumer acceptance of electronic commerce : integrating trust and risk with the technology acceptance model," *Int. J. Electron. Commer.*, vol. 7, no. 3, pp. 69–103, 2003.
36. S. Brown, A. Dennis, and V. Venkatesh, "Predicting collaboration technology use : integrating technology adoption and collaboration research," *J. Manag. Inf. Syst.*, vol. 27, no. 2, pp. 9–53, 2010.
37. M. Hartmann, E. Bäzner, B. Wild, I. Eisler, and W. Herzog, "Effects of interventions involving the family in the treatment of adult patients with chronic physical diseases: a meta-analysis," *Psychother. Psychosom.*, vol. 79, no. 3, pp. 136–148, Jan. 2010.
38. M. P. Gallant, "The influence of social support on chronic illness self-management: a review and directions for research," *Heal. Educ. Behav.*, vol. 30, no. 2, pp. 170–195, Apr. 2003.
39. V. S. Lai, "A survey of rural small business computer use: success factors and decision support," *Inf. Manag.*, vol. 26, no. 6, pp. 297–304, Jun. 1994.
40. D. Doyle, P. Cunningham, and P. Walsh, "An evaluation of the usefulness of explanation in a case-based reasoning syste for decision support in bronchiolotis treatment," *Comput. Intell. J.*, vol. 22, no. 3, 2006.
41. A. Bandura, "A social cognitive theory," *Soc. Found. thought action*, pp. 193–209, 1986.
42. A.Luse, B. E. Mennecke, and A. Townsend, "Experience richness: effects of training method on individual technology acceptance," in *Hawaii International Conference on System Sciences*, 2013, pp. 853–862.
43. J. D. Teasdale, "Self-efficacy: towards a unifying theory of behavior change," *Adv. Behav. Res.*, vol. 1, pp. 211–215, 1978.
44. P. A. Pavlou and M. Fygenson, "Understanding and predicting electronic commerce adoption : an extension of the theory of planned behavior," *MIS Q.*, vol. 30, no. 1, pp. 115–143, 2006.
45. S. A. Sivo, C. Saunders, Q. Chang, and J. J. Jiang, "How low should you go ? low response rates and the validity of inference in IS questionnaire research," *J. Assoc. Inf. Syst.*, vol. 7, no. 6, pp. 351–414, 2006.
46. J. Webster and L. Trevino, "Rational and social theories as complementary explanations of communication media choices: two policy-capturing studies," *Acad. Manag. J.*, vol. 38, no. 6, pp. 1544–1572, 1995.
47. W. Chin, B. L. Marcolin, and P. R. Newsted, "A partial least squares latent variable modeling approach for measuring interation effects," *Inf. Syst. Res.*, vol. 14, no. 2, pp. 189–217, 2003.
48. D. Gefen, D. Straub, and M. C. Boudreah, "Structural equation modeling and regression: guidlines for research practice," *AIS*, vol. 4, no. 1, p. 7, 2000.
49. M. S. Gold and P. M. Bentler, "Treatments of missing data: a Monte Carlo comparison of RBHDI , iterative stochastic regression imputation , and expectation-maximization," *Struct. Equ. Model.*, vol. 7, no. 3, pp. 319–355, 2000.

50. J. F. Hair, M. Sarstedt, T. M. Pieper, and C. M. Ringle, “The Use of Partial Least Squares Structural Equation Modeling in Strategic Management Research: A Review of Past Practices and Recommendations for Future Applications,” *Long Range Plann.*, vol. 45, no. 5–6, pp. 320–340, 2012.
51. W. Chin and P. Newsted, “Structural equation modeling analysis with small samples using partial least squares,” *Stat. Strateg. small sample Res.*, vol. 1, no. 1, pp. 307–341, 1999.
52. Fornell and J. Cha, “Partial Least Squares,” *Adv. Methods Mark. Res.*, vol. 407, pp. 52–78, 1994.
53. J. F. Hair, C. M. Ringle, and M. Sarstedt, “PLS-SEM: Indeed a silver bullet,” *J. Mark. Theory Pract.*, vol. 19, no. 2, pp. 139–152, Apr. 2011.
54. Cohen and P. Cohen, *Applied multiple regression / correlation analysis for the behavioral science*. Hillsdale, NJ: Lawrence Erlbaum Assoc., 1975.
55. F. N. Kerlinger, *Foundations of behavioral research*. New York, NY: McGraw-Hill, 1978.
56. Doll and G. Torkzadeh, “The measurement of end-user computing satisfaction,” *MIS Q.*, vol. 12, no. 2, pp. 259–274, 1988.
57. Torkzadeh and J. Lee, “Measures of perceived end-user computing skills,” *Inf. Manag.*, vol. 40, no. 7, pp. 607–615, 2003.
58. D. Gefen, D. Struab, and M. Boudrea, “Structural equation modeling and regression: guidelines for research and practice,” *Commun. AIS*, vol. 7, no. 4, pp. 1–78, 2000.
59. J. Roldan and M. Sanchez-Franco, “Variance-based structural equation modeling: guidelines for using partial least squares in information systems research,” *Inf. Sci. Ref. (an Impr. IGI Glob.*, pp. 193–221, 2012.
60. L. J. Cronbach, “Coefficient alpha and the internal structure of tests,” *Psychometrika*, vol. 16, no. 3, pp. 297–334, 1951.
61. J. C. Nunnally and I. H. Bernstein, *Psychometric theory*. New York, NY: McGraw-Hill, 1994.
62. A.E. Werts, R. L. Linn, and K. G. Joreskog, “Intraclass reliability estimates: testing structural assumptions,” *Educ. Psuchological Meas.*, vol. 34, no. 1, pp. 25–33, 1974.
63. Fornell and D. F. Larcker, “Evaluating structural equation models with unobservable variables and measurement error,” *J. Mark. Res.*, vol. 18, no. 1, pp. 39–50, 1981.\
64. A.T. Campbel and D. W. Fiske, “Convergent and discriminant validation by the mulitrait-multimethod matrix,” *Psychol. Bull.*, vol. 56, pp. 81–105, 1959.
65. C. R. Rao, *Linear statistical inference and its applications*, 2nd ed. New York, NY: Wiley, 1973.
66. W. Chin, “How to write up and report PLS analyses,” in *Handbook of partial least squares*, Handbook of partial least squares, 2010, pp. 655–690.
67. N. Urbach and F. Ahlemann, “Structural equation modeling in information systems research using partial least squares,” *J. Inf. Technol. Theory Appl.*, vol. 11, no. 2, pp. 5–40, 2010.
68. V. Vinzi, L. Trinchera, and S. Amato, “PLS path modeling: from foundations to recent developments and open issues for model assessment and improvement,” in *Handbook of partial least squares*, Springer Berlin Heidelberg, 2010, pp. 47–82.
69. M. Tenenhaus, S. Amato, and V. E. Vinzi, “A global goodness-of-fit index for PLS structural equation modeling,” in *Proceedings of the XLII SIS scientific meeting*, 2004,

vol. 1, pp. 739–742.
70. M. Wetzels, G. Odekerken, and C. van Oppen, “Using PLS path modeling for assessing hierarchical construct models: guidelines and emperical illustration,” *MIS Q.*, vol. 33, no. 1, pp. 177–195, 2009.
71. A.D. Davis, “Perceived usefulness, perceived ease of use and user acceptance of information technology,” *MIS Q.*, vol. 13, no. 3, pp. 319–340, 1989.
72. S. Brown and V. Venkatesh, “Household technology use: integrating household life cycle and the model of adotion of technology in households,” *MIS Q.*, vol. 29, no. 4, pp. 399–426, 2005.
73. N. Aldrich and W. F. Benson, “Disaster preparedness and the chronic disease needs of vulnerable older adults.,” *Prev. Chronic Dis.*, vol. 5, no. 1, pp. 27–35, Jan. 2008.

McMaster University
1280 Main St. W. DSB A202
Hamilton, ON
L8S 4M4

Tel: 905-525-9140 ext. 23956
Fax: 905-521-8995
Email: ebusiness@mcmaster.ca
Web: http://merc.mcmaster.ca