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

By

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McMaster eBusiness Research Centre (MeRC)

WORKING PAPER No. 58
June 2016
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MeRC Working Paper # 58
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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](image)

**Table 1. Construct Definition**

<table>
<thead>
<tr>
<th>Support Elements</th>
<th>Sustainability Elements</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE: Performance Expectancy</td>
<td>PPRS: Perceived Patient Reward System</td>
</tr>
<tr>
<td>EE: Effort Expectancy</td>
<td>PEAT: Perceived Usefulness - Decision Support</td>
</tr>
<tr>
<td>HM: Hedonic Motivation</td>
<td>PDS: Perceived Usefulness - Education &amp; Training</td>
</tr>
<tr>
<td>BI: Behavioral Intention</td>
<td></td>
</tr>
</tbody>
</table>

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*Figure 1. Simplified CHSMSS Model*
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>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Item Loading</th>
<th>Corrected Item-Total Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI</td>
<td>BI-1</td>
<td>0.993</td>
<td>0.881</td>
</tr>
<tr>
<td></td>
<td>BI-2</td>
<td>0.992</td>
<td>0.869</td>
</tr>
<tr>
<td>HM</td>
<td>HM-1</td>
<td>0.933</td>
<td>0.842</td>
</tr>
<tr>
<td></td>
<td>HM-2</td>
<td>0.971</td>
<td>0.797</td>
</tr>
<tr>
<td></td>
<td>HM-3</td>
<td>0.942</td>
<td>0.861</td>
</tr>
<tr>
<td>PE</td>
<td>PE-1</td>
<td>0.991</td>
<td>0.870</td>
</tr>
<tr>
<td></td>
<td>PE-2</td>
<td>0.992</td>
<td>0.889</td>
</tr>
<tr>
<td>EE</td>
<td>EE-1</td>
<td>0.968</td>
<td>0.882</td>
</tr>
</tbody>
</table>
**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>
<thead>
<tr>
<th>Construct</th>
<th>AVE</th>
<th>Composite Reliability (CR)</th>
<th>Cronbach’s Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI: Behavioural Intention</td>
<td>0.985</td>
<td>0.993</td>
<td>0.985</td>
</tr>
<tr>
<td>EE: Effort Expectancy</td>
<td>0.931</td>
<td>0.964</td>
<td>0.926</td>
</tr>
<tr>
<td>HM: Hedonic Motivation</td>
<td>0.900</td>
<td>0.964</td>
<td>0.945</td>
</tr>
<tr>
<td>PDS: Perceived Decision</td>
<td>0.919</td>
<td>0.972</td>
<td>0.956</td>
</tr>
<tr>
<td>Support</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE: Performance Expectancy</td>
<td>0.983</td>
<td>0.991</td>
<td>0.983</td>
</tr>
<tr>
<td>PEAT: Perceived Ed. &amp;</td>
<td>0.949</td>
<td>0.974</td>
<td>0.947</td>
</tr>
<tr>
<td>Training</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPRS: Perceived Patient</td>
<td>0.987</td>
<td>0.994</td>
<td>0.987</td>
</tr>
<tr>
<td>Reward System</td>
<td></td>
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</tbody>
</table>
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

<table>
<thead>
<tr>
<th>Item</th>
<th>BI</th>
<th>EE</th>
<th>HM</th>
<th>PDS</th>
<th>PE</th>
<th>PEAT</th>
<th>PPRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI-1</td>
<td>0.992</td>
<td>0.545</td>
<td>0.795</td>
<td>0.742</td>
<td>0.784</td>
<td>0.689</td>
<td>0.826</td>
</tr>
<tr>
<td>BI-2</td>
<td>0.992</td>
<td>0.538</td>
<td>0.793</td>
<td>0.728</td>
<td>0.767</td>
<td>0.675</td>
<td>0.817</td>
</tr>
<tr>
<td>EE-1</td>
<td>0.521</td>
<td>0.967</td>
<td>0.682</td>
<td>0.552</td>
<td>0.586</td>
<td>0.490</td>
<td>0.554</td>
</tr>
<tr>
<td>EE-2</td>
<td>0.533</td>
<td>0.961</td>
<td>0.663</td>
<td>0.491</td>
<td>0.483</td>
<td>0.389</td>
<td>0.503</td>
</tr>
<tr>
<td>HM-1</td>
<td>0.762</td>
<td>0.650</td>
<td>0.933</td>
<td>0.745</td>
<td>0.786</td>
<td>0.744</td>
<td>0.769</td>
</tr>
<tr>
<td>HM-2</td>
<td>0.763</td>
<td>0.706</td>
<td>0.970</td>
<td>0.688</td>
<td>0.715</td>
<td>0.691</td>
<td>0.736</td>
</tr>
<tr>
<td>HM-3</td>
<td>0.751</td>
<td>0.629</td>
<td>0.942</td>
<td>0.653</td>
<td>0.676</td>
<td>0.666</td>
<td>0.743</td>
</tr>
<tr>
<td>PDS-1</td>
<td>0.706</td>
<td>0.525</td>
<td>0.695</td>
<td>0.945</td>
<td>0.772</td>
<td>0.757</td>
<td>0.698</td>
</tr>
<tr>
<td>PDS-2</td>
<td>0.708</td>
<td>0.507</td>
<td>0.699</td>
<td>0.965</td>
<td>0.817</td>
<td>0.754</td>
<td>0.685</td>
</tr>
<tr>
<td>PDS-3</td>
<td>0.716</td>
<td>0.528</td>
<td>0.717</td>
<td>0.966</td>
<td>0.798</td>
<td>0.785</td>
<td>0.717</td>
</tr>
<tr>
<td>PE-1</td>
<td>0.770</td>
<td>0.526</td>
<td>0.748</td>
<td>0.818</td>
<td>0.991</td>
<td>0.779</td>
<td>0.771</td>
</tr>
<tr>
<td>PE-2</td>
<td>0.780</td>
<td>0.576</td>
<td>0.769</td>
<td>0.828</td>
<td>0.991</td>
<td>0.788</td>
<td>0.768</td>
</tr>
</tbody>
</table>
### Table 5. Construct Correlation Matrix

<table>
<thead>
<tr>
<th>Item</th>
<th>BI</th>
<th>EE</th>
<th>HM</th>
<th>PDS</th>
<th>PE</th>
<th>PEAT</th>
<th>PPRS</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI</td>
<td>0.991</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EE</td>
<td></td>
<td>0.965</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HM</td>
<td>0.800</td>
<td>0.697</td>
<td>0.949</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PDS</td>
<td>0.740</td>
<td>0.542</td>
<td>0.734</td>
<td>0.959</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td>0.781</td>
<td>0.556</td>
<td>0.765</td>
<td>0.830</td>
<td>0.991</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PEAT</td>
<td>0.687</td>
<td>0.458</td>
<td>0.739</td>
<td>0.798</td>
<td>0.790</td>
<td>0.974</td>
<td></td>
</tr>
<tr>
<td>PPRS</td>
<td>0.828</td>
<td>0.549</td>
<td>0.790</td>
<td>0.730</td>
<td>0.776</td>
<td>0.683</td>
<td>0.993</td>
</tr>
</tbody>
</table>

### 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 ($\beta$):** 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**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Path</th>
<th>Path Coefficient</th>
<th>t-Stat</th>
<th>Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>PDS $\rightarrow$ PE</td>
<td>0.550</td>
<td>6.024 ***</td>
<td>Supported</td>
</tr>
<tr>
<td>H2a</td>
<td>PEAT $\rightarrow$ PE</td>
<td>0.352</td>
<td>3.754 ***</td>
<td>Supported</td>
</tr>
<tr>
<td>H2b</td>
<td>PEAT $\rightarrow$ EE</td>
<td>0.458</td>
<td>5.109 ***</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>PPRS $\rightarrow$ HM</td>
<td>0.791</td>
<td>5.283 ***</td>
<td>Supported</td>
</tr>
</tbody>
</table>
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:

\[
f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{1 - R^2_{\text{included}}}
\]

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>PE</th>
<th>EE</th>
<th>HM</th>
<th>BI</th>
</tr>
</thead>
<tbody>
<tr>
<td>PDS</td>
<td>0.415</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PEAT</td>
<td>0.170</td>
<td>0.266</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPRS</td>
<td></td>
<td></td>
<td>0.625</td>
<td></td>
</tr>
<tr>
<td>PE</td>
<td></td>
<td></td>
<td></td>
<td>0.242</td>
</tr>
<tr>
<td>EE</td>
<td></td>
<td></td>
<td></td>
<td>non-sig.</td>
</tr>
<tr>
<td>HM</td>
<td></td>
<td></td>
<td></td>
<td>0.284</td>
</tr>
</tbody>
</table>

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>
<thead>
<tr>
<th>Endogenous Variables</th>
<th>($Q^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PE (Performance Expectancy)</td>
<td>0.717</td>
</tr>
<tr>
<td>EE (Effort Expectancy)</td>
<td>0.189</td>
</tr>
<tr>
<td>HM (Hedonic Motivation)</td>
<td>0.560</td>
</tr>
<tr>
<td>BI (Behavioural Intention)</td>
<td>0.697</td>
</tr>
</tbody>
</table>
**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:

\[
GOF = \sqrt{\text{Commmunality} \times R^2} = \sqrt{(0.9497) \times (0.5702)} = 0.7359
\]

**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>
<thead>
<tr>
<th>Variables</th>
<th>PE</th>
<th>EE</th>
<th>HM</th>
<th>BI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.004</td>
<td><strong>0.102</strong></td>
<td>0.004</td>
<td>0.000</td>
</tr>
<tr>
<td>Gender</td>
<td>0.000</td>
<td>0.007</td>
<td>0.000</td>
<td>0.004</td>
</tr>
<tr>
<td>Educational Background</td>
<td>0.000</td>
<td>0.025</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Hours of Internet Use</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.000</td>
</tr>
<tr>
<td>Smartphone Access</td>
<td>0.000</td>
<td>0.014</td>
<td>0.004</td>
<td>0.012</td>
</tr>
</tbody>
</table>

**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>
<thead>
<tr>
<th>Type of Concern</th>
<th>Number of Answers</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Too much effort</td>
<td>49</td>
<td>~ 49 %</td>
</tr>
<tr>
<td>Lack of need</td>
<td>22</td>
<td>~ 22 %</td>
</tr>
<tr>
<td>Security &amp; Privacy</td>
<td>20</td>
<td>~ 20 %</td>
</tr>
<tr>
<td>Other concerns</td>
<td>10</td>
<td>~ 10 %</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ Making it more automated to eliminate data entry, so less effort and time would be needed</td>
</tr>
<tr>
<td>➢ Support for more specific conditions</td>
</tr>
<tr>
<td>➢ Linking the system to the systems of official healthcare providers</td>
</tr>
<tr>
<td>➢ Adding a professional fitness trainer</td>
</tr>
<tr>
<td>➢ Patients should be able to see what others with similar condition are doing, rather than just what they choose to post online</td>
</tr>
<tr>
<td>➢ Education for the care partner too</td>
</tr>
</tbody>
</table>

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 ($PE \rightarrow BI$) and also between effort expectancy of the system and behavioural intentions ($EE \rightarrow BI$) as well as hedonic motivation and behavioural intention ($HM \rightarrow BI$). However, while there was a significant relation between $PE \rightarrow BI$ ($\beta=0.411, f^2=0.242$) and $HM \rightarrow BI$ ($\beta=0.515, f^2=0.284$), there was no significant relationship between $EE \rightarrow BI$.

It is obvious that while the $PE \rightarrow BI$ and $HM \rightarrow BI$ 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 ($\beta=0.339, f^2=0.351$). 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 $PDS \rightarrow PE$ ($\beta=0.550$, $f^2=0.415$) and $PEAT \rightarrow PE$ ($\beta=0.352$, $f^2=0.170$) 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 ($PEAT \rightarrow EE$: $\beta=0.458$, $f^2=0.266$) 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 ($PEAT \rightarrow HM$: $\beta=0.321$, $f^2=0.243$), 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 ($PPRS \rightarrow HM$: $\beta=0.791$, $f^2=0.625$) 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 ($\beta=-0.261$, $f^2=0.102$). 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


32. V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of


