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The Clinical Impact of eHealth on the Self-Management of Diabetes: A Double Adoption Perspective

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Abstract

The development, adoption, and acceptance of eHealth systems that change and improve patient self-care have been promising, but the results have been mixed and the work mostly atheoretical. In this paper, we respond to this opportunity by developing and assessing an eHealth system for newly diagnosed type 2 diabetes patients. Study participants used the eHealth system for a 12-month period after diagnosis in an attempt to acquire an understanding about their diabetes, develop self-care activities (e.g., blood glucose testing), and improve their biomedical outcomes. Drawing upon theories and methods from information systems and upon the Precede-Proceed model of health promotion planning, we explored the double adoption of eHealth technology and its antecedents, self-care practices and their antecedents, and improvements in biomedical outcomes important to long-term diabetes health. Path model results indicate important implications for information systems, eHealth, and health promotion practice and research, which are discussed.

Keywords: *Adoption, IT Use, ehealth, Internet, Diabetes, Education, Attitudes, Behavior, Health Outcomes.*

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1. Introduction

The development, adoption, and acceptance of eHealth systems in changing and improving clinician and patient practices in coordinating self-care have been both promising and difficult. Wickrmasinghe, Geisler, and Schaffer (2005) suggest that many eHealth system implementations may address "complex challenges in trying to deliver cost-effective, high-value, accessible healthcare" (p. 294), but these systems also face numerous problems and the health care sector appears "slow to embrace new business techniques and technologies" (p. 294).

In terms of promises, the trends in the global use of the Internet suggest that patients may be both ready and capable of using eHealth systems for improving their care. Eng (2001) defines eHealth as the use of emerging information and communications technology, especially the Internet, to improve or enable health provision and to facilitate the improvement of individual health. According to the Pew Foundation (as cited in Madden and Fox, 2006), approximately 80 percent of Internet users access health information online, and this information influences their health care decisions and interactions with health care providers.

In response, various attempts to build and adopt information systems (IS) have been aimed at taking advantage of this growing Internet connectivity and use through "eHealth." A number of eHealth systems focusing on education have been accepted and rapidly adopted by health organizations, health care providers, and patients because of perceived cost savings, convenience, and access to information from remote locations (Dawson, 2002). Until recently, studies have shown little difference between eHealth treatment groups and traditional face-to-face control groups in terms of health outcomes (Azar & Gabbay, 2009). This lack of difference combined with the related resource utilization benefit and the increased reach of these systems provide evidence that these technologies are useful. However, the theoretical pathways from eHealth systems use to health-related behaviors, and from the behaviors to health outcomes, have remained largely under studied at both group and individual levels. Therefore, the goals of this study are to highlight what factors affect eHealth use, how eHealth use affects the antecedents of self-care behaviors in chronic disease education and management, and how changes in self-care behaviors affect biomedical outcomes.

IS research has much to offer the theoretical and analytical areas outlined above. Santhanam, Sasidharan, and Webster (2008) specifically state that "IS researchers, with their multidisciplinary focus and ability to integrate social and cognitive processes with technology affordances, are uniquely qualified to study TML [technology-mediated learning]" (p. 27). This statement is pertinent to eHealth for two reasons. IS researchers have much to offer eHealth with its important focus on patient learning and chronic self-care. In addition, IS researchers are qualified to study how the different functionality of eHealth systems impacts chronic disease management. These technologies can range from static content, such as articles for self-directed and self-paced learning about a condition, to continuous and dynamic capture of patient-specific outcomes, and to the asynchronous or synchronous communication of information between patients and clinicians or with other patients.

As the IS field uses numerous theoretical and statistical techniques for technology adoption, eHealth research can benefit from this core understanding, particularly as it relates to the individual factors affecting information technology (IT) adoption and use in eHealth (Fichman, Kohli, & Krishnan, 2008). We employed various theories and instruments from IS to inform our study and the results.

At the same time, the research in eHealth has much to offer IS researchers who have been calling for an increased focus on eHealth to further their understanding of theoretical issues (e.g., economic, behavioral, strategic, and organizational) in this unique setting (Fichman et al., 2008). We also believe that conducting research on the detailed behavioral aspects of eHealth can provide important empirical results and theoretical ideas to inform important issues in the IS field. In particular, IS-informed eHealth research can compare similarities and differences in eHealth adoption and use with other IS diffusion research examining information technologies within other contexts. Developing an understanding of the contextual differences will benefit the further development of IS theory by refuting, extending, or modifying existing theory, or by developing new theories and revealing important and general phenomena in a context where it can be more easily revealed.

More importantly, the focus on individual behavioral and biomedical outcomes in eHealth can also address the important quest for the dependent variable in IS research (DeLone & McLean, 1992) by investigating the direct role of the IT artifact in connecting improved computer systems to better information, changes in behavior, and changes in biomedical outcomes that will lead to improved health. To aid the quest for the dependent variable and to realize the co-informing of the eHealth and IS domains, we explore the antecedents to the adoption of an eHealth system by individuals newly diagnosed with type 2 diabetes and the affect of individual-level eHealth use on the antecedents to the self-care behaviors that affect health outcomes.

Diabetes is a substantial concern globally with an anticipated growth that is now considered to be epidemic (Canadian Diabetes Association [CDA], 2009). A staggering 439 million adults globally are predicted to develop diabetes by 2030 (Shaw, Sicree, & Zimmet, 2010) including an increasing number of younger and working individuals. The increase in health care costs associated with diabetes is also considerable, reaching a treatment cost of $232 billion USD in 2007 (Novo Nordisk, 2009). A considerable increase is expected as the anticipated 439 million people with diabetes place an enormous burden on the world's health care systems. Given these estimates, one can understand why governments and health care providers are actively searching for cost effective treatment options such as eHealth (Advisory Council on Health Infostructure, 1999).

This study employs a health promotion theory, the Precede-Proceed health promotion model (PPM) (Green & Kreuter, 1991, 2005) and various IS theories and methods to analyze a proposed model of the double adoption of an eHealth system and self-care behaviors. We designed and used an eHealth system to collect and measure antecedents to eHealth system use, actual system use, antecedents of self-care behaviors, reported self-care behaviors, and health outcomes every three months over a 12-month period. Although PPM has the potential to add an important contribution to both eHealth and IS research, to date it has received little attention by IS researchers. The eHealth system, developed by our research team in consultation with a diabetes education clinic, includes electronic educational materials, interactive tools to communicate with clinicians, and tools for patient and patient-clinician capture of personal health information as well as diabetes outcomes monitoring capabilities.

In the next section, we describe how the IS literature and PPM inform the development of our double adoption model. We then report on our longitudinal and experimental study with type 2 diabetes patients using a custom-built eHealth system. Next we present the individual-level path model results, and we conclude the paper by considering the research and practical implications of the double adoption of IT use and its influence on self-care behaviors and health outcomes.

2. Research Framework

In this section, we review the key IS literature on technological adoption and acceptance that informed our study and introduce the PPM of health promotion planning. In providing a comparative contrast to adoption theories in the IS literature, our application of Precede-Proceed organizes various attitudinal and knowledge-related antecedents to IT use into what are called predisposing-reinforcing-enabling (PRE) antecedents of behavior in PPM. We then illustrate how eHealth use affects the PRE antecedents to self-care practices. The effects of self-care behaviors on health are the final pathway in the complete model.

2.1. Measures and Theories of IT Adoption in IS

Various theories and models have been constructed to explore the adoption and use of IT in the IS literature. In an attempt to synthesize a number of them, Venkatesh, Morris, Davis, and Davis's (2003) Unified Theory of Acceptance and Use of Technology (UTAUT) incorporates a number of theories: the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis, 1989), the Motivational Model (Davis, Bagozzi, & Warshaw, 1992), the Theory of Planned

Behavior (Ajzen, 1991; Taylor & Todd, 1995), a combination of TAM and the Theory of Planned Behavior (Taylor & Todd, 1995), Innovation and Diffusion Theory (Moore & Benbasat, 1991; Rogers, 1995), and Social Cognitive Theory (Compeau & Higgins, 1995a, 1995b). In summarizing these various theoretical influences, the UTAUT model points to three main influences on the adoption of IT: performance expectancy (i.e., what will be the results of use and what will be the value of those results), effort expectancy (i.e., what work will be involved in using the technology, and do I have the capabilities to do so), and social influences (i.e., what will others expect of me). These antecedents are considered important in affecting behavioral intentions to IT use, which, in turn, influences actual use.

More recent research has focused on teasing apart these foundational theories. For example, Au, Ngai, and Cheng (2008) show that performance expectations do not fully explain end-user satisfaction with IT and that a consideration of the ratio between effort and the satisfaction of particular needs during IT use (work performance, relatedness, and self-development) explains end-user satisfaction. Similarly, Venkatesh, Brown, Maruping and Bala (2008), building on Burton-Jones and Straub's (2006) work, focus on three different measures of use (duration, frequency, and intensity) and the role of behavioral expectation (which takes into account users' expectations for use given facilitating conditions) as a mediating link from behavioral intention to the different forms of use. Other researchers have focused on various attitudes about the compatibility of the technology (i.e., work, prior experience, and values) and their influence on use (Karahanna, Agarwal, & Angst, 2006). Much of this work follows calls for redirecting and reshaping IS adoption research. For example, past calls suggest a need to focus more on the performance impacts of IT adoption rather than just the quantity of adoption (Fichman, 2004).

We used eHealth as one step in addressing this limitation in the research area by drawing upon the PPM to reconceptualize the antecedents to and outcomes from IT use on health-related behaviors. In the next section, we describe the PPM and discuss how we used this model to encompass not only antecedents to health behaviors, but also antecedents to the adoption and use of eHealth systems, in an attempt to jointly inform eHealth, health promotion, and IS research.

2.2. The Precede-Proceed Model

PPM focuses health planners and researchers on the development of health promotion and educational programs that affect the antecedents of health behaviors and the environment and affect the resulting health and quality-of-life of a population of people (Green & Kreuter, 1991, 2005). PPM is a broad and action-oriented model that comprises two components—the precede phases of developing a plan of action through these pathways, and the proceed phases for implementing educational interventions that will affect these pathways. In addition, PPM is a general model that can be shaped to fit a specific health area. As a result, the program planner and researcher construct specific path models, which include the factors and causal relations between the paths, to address particular components of a health program (Green & Kreuter, 2005, p. 149). PPM is a well-established and rigorous meta-model that is widely used and applied in health promotion research and practice (see Green, 2010).

PPM, when applied and shaped specifically for health promotion and planning, builds on theories similar to those used in the IS adoption literature (e.g., the theory of reasoned action, social learning, etc.). PPM differs, however, in organizing attitudinal, behavioral, and enabling conditions that affect behavior into "predisposing, reinforcing, and enabling constructs in educational/ecological diagnosis and evaluation" (Green & Kreuter, 2005, p. 9), with a dominant focus on health behaviors as well as health and quality-of-life outcomes (not behavioral intentions to use or individual satisfaction per se). A subset of a generic PPM for health program planning and evaluation is presented in Figure 1. This generic model depicts the central causal associations.

Green and Kreuter (2005) theorize that PRE groups of causal factors are important meta-categories of factors that influence individual and population behaviors. Predisposing factors are individual characteristics and attitudes that provide the motivation, which facilitates or hinders the likelihood of behavioral change. These factors (e.g., knowledge, attitudes, beliefs, values, and perceptions) facilitate or hinder motivation for change (Green & Kreuter, 2005, p. 14). Reinforcing factors relate to negative and positive feedback from the effects of behaviors, which can facilitate or hinder their continuation. These can include feedback about performance, encouragement, physical pain, peer influences, and rewards (Green & Kreuter, 2005, p. 14). Enabling factors, often related to the environment or system, are the prevalence or absence of key resources and capabilities that are required to facilitate a behavior. Examples include the accessibility (i.e., cost) and availability of health care and community resources, availability of referrals services, the access to training and skills for behavior, and new skills needed to carry out the behavior (Green & Kreuter, 1991). “The three conditions – predisposing, enabling, and reinforcing – must be aligned for the behavior to occur and persist” (Green & Kreuter, 2005, p. 148). These meta-categories of predisposing, reinforcing, and enabling include an array of factors that either increase or decrease the likelihood of the behavior (Green & Kreuter, 1991). All three are necessary for individual behavior to change, and, thus, all three not only influence behavior, but may also impact each other depending upon the health-related behavior or environmental change.

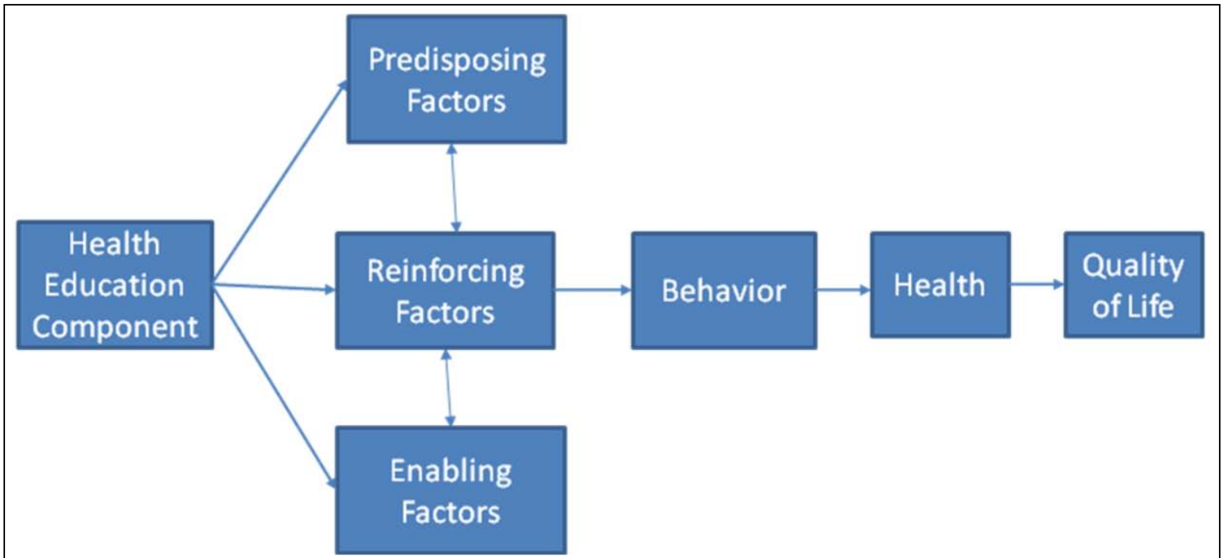

Figure 1. Subset of the Generic Precede-Proceed Model (Green & Kreuter, 2005, p. 10)

For more than three decades, PPM has served as a robust theoretical lens for health promotion interventions and medical field trials (Green & Kreuter, 2005). The extant literature provides evidence for the application of PPM to explain and influence human behaviors in numerous health contexts such as asthma (Chiang, Huang, Yeh, & Lu, 2004), oncology (Schofield, Carey, Bonevski, & Sanson-Fisher, 2006), and arthritis (Lacaille et al., 2008). Green and Kreuter (2005) state, “The classification of predisposing, enabling, and reinforcing determinants of behavior offers a broad framework within which one can organize and apply more specific theories and research” (p. 148). In comparison with the IS literature, predisposing factors capture many of the antecedents measured in IS adoption (e.g., individual attitudes toward the behavior). However, predisposing also encompasses both perceptual and non-perceptual individual characteristics often considered to be separate and distinct, such as knowledge. Reinforcing factors focus on how new behaviors are intensified by positive and negative feedback from attempts to behave differently, including the feedback of peers, family, and other people around the individual, and physiological pain or pleasure. In the IS field social influences have been largely studied separately, considering these social influences as a part of the feedback from initial behavior in PPM is a contribution to the IS literature. Finally, enabling factors focus on individual and contextual conditions that facilitate or hinder use, including individual skills, resource access, and access to training.

Green and Kreuter's (2005) broad framework of the meta-categories was based on and allows for the application of more specific theories and research (e.g., diffusion and adoption theory and models of change) within it (p. 148). We argue that the predisposing, reinforcing, and enabling factors (the PRE component) of PPM are of theoretical and practical interest to both eHealth use—in this case a web-based system for electronic health education materials, interactive discussions with clinicians, and the active collection and monitoring of individual activities and information—and to diabetes self-care practices. The theoretical relationships of this double diffusion are depicted in Figure 2 using PPM.

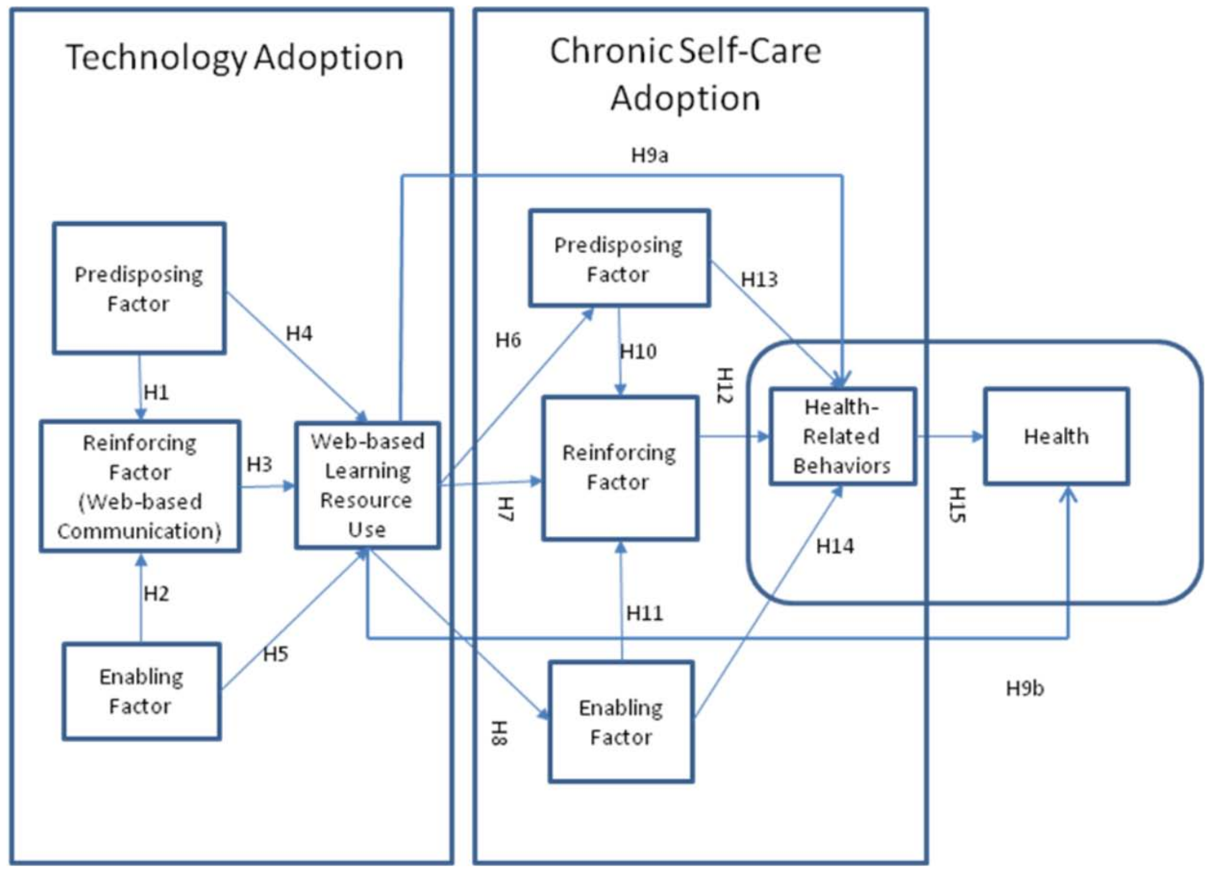

Figure 2. Proposed Research Model Based on Subset of the Generic Precede-Proceed Model

As one of our goals is an initial development and test of our proposed double adoption model, and given the comprehensive nature of PPM, we decided to reduce the nomological complexity by focusing on only one set of PRE factors, using previously validated measures from the IS and diabetes education literatures, and modeling these relationships as recursive. We elected to focus on well-established associations in the literature. The antecedents to eHealth adoption are highlighted in Technology Adoption section in Figure 2, using the PRE factors that would influence web system use. The hypotheses are outlined in Appendix A. Using the PRE component of PPM, Hypotheses 1 through 5 test whether there is an influence of a predisposing factor on a reinforcing factor (i.e., web-based communication) for web system adoption (H1), an enabling factor on a reinforcing factor (i.e., web-based communication) for web system adoption (H2), and of the antecedent factors on web-based learning resource use (H3 to H5) for web system adoption. Our proposed model assumes that both enabling and predisposing conditions may support the reinforcement of behavior.

The antecedents to the adoption of self-care behaviors highlighted in Chronic Self-Care Adoption section in Figure 2 use PRE factors for self-care behaviors. Hypotheses 10 and 11 test whether predisposing and enabling factors affect a reinforcing factor for self-care behavior, and Hypotheses 12 to 14 test whether there is a relationship between the antecedents of self-care behavior and health-related behaviors.

In a more exploratory step, and as a contribution to the eHealth and IS adoption literature, we then connect the two adoption models through web-based learning resource use and the antecedent factors of self-care behavior and from web-based learning resource use directly to health. Hypotheses 6 through 9 explore and test these theoretical associations building on Green and Kreuter (1991, 2005). We hypothesize that use of the web-based learning resource will be associated with changes in the antecedents to self-care behavior (H6 to H8), but also that web-based learning resource use can affect self-care behavior (H9a) and health outcomes directly (H9b). The combination of Hypotheses 6 through 12 tests the influence of web-based learning resource use on self-care behaviors and health outcomes. Finally, Hypothesis 15 tests the assumed relationships in PPM between the changes in health-related behaviors and the changes in health outcomes.

Each of our hypotheses is theoretically justified with the direction of the relationships, depending upon the factors and measures selected and the specifics of the health context. Therefore, we elected to follow Chin's (1998) recommendation to avoid providing directional hypothesis statements for each path depicted in our theoretical framework. Our fully stated hypotheses (in the null form), including the measures used to assess each, are included in Appendix A for the reader's interest. We turn to our research method next for empirically evaluating this model of eHealth and self-care behavioral adoption.

3. Research Method

We conducted a longitudinal field experiment, which was blind to the patients, to test our hypotheses. The field experiment involved the use of an eHealth system for patient education, monitoring patient activities and results, and patient–clinician feedback for newly diagnosed type 2 diabetes patients from a health region in Canada. Creating a web system to educate people newly diagnosed with type 2 diabetes had multiple motivations. The vast geography of Canada isolates some of the population from face-to-face contact with health care professionals. In addition, with younger people now developing diabetes, face-to-face education classes may interrupt their working day. We were also motivated by the possibilities of extending the IS and eHealth research in patient self-care.

3.1. Participants and Recruitment

Participants were adult patients who had been referred by their physicians to a Building Healthy Lifestyle (BHL) program. The BHL program educates patients by teaching basic knowledge about diabetes and self-care activities, specific self-care strategies given the patient's diagnosis, and the self-management and monitoring skills required by patients to improve their self-care management techniques. Before this study, this education was accomplished face-to-face through an initial and subsequent dialogue with the patient via education meetings and/or classes at the time of diagnosis, and subsequent visits and telephone calls concerning blood sugar results, biomedical tests, and the effectiveness of the patient's developed self-care behaviors.

For this study we recruited individuals who were newly diagnosed with type 2 diabetes and were referred to the BHL by their general practitioners. Potential participants were screened to ensure that they had access to a computer connected to the Internet, were computer literate, had no other complicating health conditions (including pregnancy), and were not involved in another research study. To experimentally assess the eHealth intervention, we developed an eHealth system with educational materials with the ability to record patient activities and outcomes and the ability to interact with BHL clinicians and patients. We report here on the path model results for a treatment group called the interactive group of patients who received the widest range of web-system functionality. BHL patients were randomly assigned to this treatment, were unaware of the other treatments or other participants, and were asked not to discuss their participation in the study with other non-medical individuals.

The web system developed for the interactive treatment group included utilities, educational materials, and both asynchronous and synchronous tools for communication (see Figure B1 in Appendix B for an image of the home page and Figure B2 in Appendix B for an image of the learning material page). The functionalities of these components are listed in Table 1. We categorized the functionalities of the web system into utilities, web-based learning resources, and web-based communication between participants and clinicians. In addition, a system was developed to support clinicians' interactions with their patients (e.g., e-messaging, chats, and access to individual patients' blood glucose journals). We developed these various systems during a separate research phase using an action research methodology.

Table 1. List of eHealth Functionalities

Components	Functionalities
Utilities	Change Password
	Update Your Profile
	Training Materials
Web-Based Learning Resource	Educational Materials
	Internet Search (connected to Google)
	Track Your Own Learning
	Vetted Web Links (by Clinicians)
	Bulletin Board
	Blood Glucose Journal
	HbA1c Results
	Lab and Medication Updates
	Updating Oral and Injected Medications
	Reminders
	Message Centre – important notes from Building Healthy Lifestyles program
Patient–Clinician Web-Based Communication	E-messaging
	Chat Rooms – Private and Public

The blood glucose (BG) journal allowed patients to record their hourly self-care activities and BG values (see Figure B3 in Appendix B for image of BG journal page). The journal allowed us to track when the participants' BG values were too low (< 5), normal (5 to 7), or too high (> 7). The BG journal also helped to identify two-week low or high trends across each day.

Patients also attended "virtual appointments" with their clinicians. Each participant sent e-messages that included questions and comments to his or her clinician the day before an asynchronistic virtual appointment or booked a private chat room with the clinician to enable a synchronistic virtual visit. During the scheduled time of the virtual appointment, the clinician replied to the participant's questions and comments using the e-messaging system or during the private chat. In addition, the clinician reviewed the participant's BG journal and provided comments and advice based on his or her blood sugar values. Participants could send e-messages to their clinicians between their virtual appointments if they felt it was necessary.

Due to the number of physician referrals to the program, we used a rolling recruitment strategy over an 18-month period. All individuals who entered the BHL participated in an initial face-to-face assessment session (approximately 45 to 60 minutes) with a trained clinician. A total of 29 patients were recruited to this interactive group; we were unable to obtain demographic data for two of the participants. Of the 29 participants who volunteered for the experiment, 18 lived in an urban center, and 12 were male and 15 were females. Their ages ranged from 39 to 89 years of age (Mean = 56 years of age). Participants received no monetary benefit for their participation in the experiment. All participants completed the outcome instruments when they entered the study (baseline) followed by four additional time intervals (three, six, nine, and 12 months) during the 12-month period. System logs captured participants' use of various functionalities of the web system continuously. In total, we obtained 95 observations.

All participants received face-to-face eHealth system training and a training manual. The trainer at the training sessions obtained written consent for participation from each of the participants. The technology trainer used standardized scripts during his or her interaction with participants. During training, participants were assigned a unique user name and password for accessing the web system and completed experimental study instruments and lab and medication questions. Training sessions were approximately 60 minutes in duration. Each participant received a copy of his or her user name and password and four lab requisition forms for HbA1c tests, which is a laboratory test that captures the average level of blood sugar control over the last three months (Canadian Diabetes Association, 2008).

3.2. Measures

As previously outlined, we decided to reduce the nomological complexity by focusing on only one set of PRE factors for each adoption area by using previously validated measures from the IS and diabetes education literatures.

3.2.1. Technology Adoption Variables

Previously validated IS measures were used to measure predisposing and enabling factors for technology adoption. These measures are described below.

We measured the predisposing factor by adapting Compeau and Higgins' (1995b) measurement of application-specific computer self-efficacy (CSE). Given the PRE model, CSE is a predisposing factor because a person's self-efficacy beliefs affect his or her predisposition to use the system. We used a 10-point confidence scale for the measure, ranging from 1 (not at all confident) to 10 (totally confident); see the Appendix C for a list of the items. This measure has consistently demonstrated excellent psychometric properties (i.e., validity and reliability) in the IS literature. We collected responses for CSE at Time 0 (baseline or T0) and then on a quarterly basis for 12 months (T1, T2, T3, and T4).

The reinforcing factor of web-based communication (i.e., the total number of chats and e-messages with clinicians since the last measurement) was continuously captured by system logs, which were then summarized by related quarter (T1, T2, T3, and T4). The chats and e-messages are functions of the system; the frequent use of these functions suggests that there was information communication and feedback between the patients and clinicians. Green and Kreuter (2005) theorize that specific behaviors in and of themselves become reinforcing factors on future behaviors. Given this, the chats and e-messages were forms of reinforcement where clinicians and patients could reinforce continued use of the system (i.e., use of these particular functionalities would reinforce future use of the system). To ensure separation from the web-based learning resource use measure, we did not include chat and e-message use in the web-based learning resource use measure in order to avoid autocorrelation.

Green and Kreuter (2005) suggest that an enabling factor of personal skills such as self-care may foster specific health behaviors. Extrapolating this theoretical conjecture to the IT adoption section of our proposed model, we felt that IT knowledge, rather than other technology skills, was the most important factor for using the web system. An individual needs to have sufficient IT knowledge in order to use the web system for its intended purpose (i.e., diabetes education). The enabling factor was measured by an adapted version of the User Competence Questionnaire (UCQ) (Marcolin, Compeau, Munro, & Huff, 2000; Munro, Huff, & Marcolin, 1997). Given the PRE categories, competence is an enabling factor for web system use because it is a resource the individual draws upon to encourage use (as opposed to an attitude that predisposes use). The UCQ consists of two dimensions: knowledge (breadth and depth) and finesse. The coefficient for internal consistency of this measurement instrument is 0.86 (Munro et al., 1997). We elected to measure only the knowledge dimension because this subscale assesses how well users of computer technologies know a particular application or tool (see Appendix C for a list of items). The anchors for the 7-point scale for the knowledge dimension ranged from 0 (no knowledge) to 7 (complete knowledge). Responses for UCQ were collected at Time 0 (baseline or T0) and then on a quarterly basis for 12 months (T1, T2, T3, and T4).

We calculated the web-based learning resource by using system logs to continuously capture the number of times participants accessed web pages on the eHealth system across the learning functionalities, which were then summarized into a total for the related quarter (T1, T2, T3, and T4). Given both PPM and the IS research, this total web-based learning resource use allowed us to measure the actual system learning behavior of the users. Web-based learning resource use also allowed us to assess the final outcome measure of the first stage of the double adoption (technological adoption and acceptance), which we then hypothesized to affect the second stage of adoption (chronic self-care adoption).

3.2.2. Chronic Self-Care Adoption Variables

We measured the predisposing and enabling factors of chronic self-care adoption by previously validated measures adapted from the diabetes literature. Patients completed responses for these two measures at baseline (T0) and at each quarter (T1, T2, T3, and T4).

We measured the predisposing factor using diabetes self-efficacy (DSE) (Littlefield et al., 1992). Given PPM, efficacy about diabetes self-care is a predisposing factor for self-care behaviors (e.g., blood sugar testing, exercise, etc.) because people's perceptions of their ability to carry out such behaviors predisposes them to carry out those behaviors. We used a 10-point confidence scale ranging from 1 (not at all confident) to 10 (totally confident) to assess the five items of this measurement.

We measured the reinforcing factor using the average BG value entered by participants in their electronic journals since the last measurement quarter (T1, T2, T3, and T4). Given the PRE factors, a change in BG values should reinforce self-care behavioral practices because it provides an indication of the patient's metabolic control.

We assessed the enabling factor of self-care behavior using the diabetes knowledge test (Fitzgerald et al., 1998). Given the PRE factors, knowledge of diabetes is a predisposing factor because a person's knowledge of diabetes and self-care behaviors should enable him or her to carry out these behavioral activities. This test consisted initially of 23 multiple-choice questions that tested participants' level of knowledge about diabetes and self-care management practices. Each participant answered questions related to his or her category of diabetes (i.e., life style changes, medication, or insulin). Each participant's knowledge score was calculated as the percentage of correct responses to the multiple-choice questions. We then summarized the 23 measures into a percentage score of correct answers.

3.2.3. Behavioral and Health Outcomes

We used a previously validated measure—of diabetes self-care activities--to measure self-care behaviors (Toobert, Hampson, & Glasgow, 2000). We included a 5-point scale ranging from 1 (always used) to 5 (never used). For analysis purposes, we reversed the sign of the path coefficients to eliminate misinterpretation. Our hypotheses measure whether there was an effect on self-care behaviors due to other factors. Self-care behaviors include blood sugar testing and treatment of low blood sugars (< 5) using specific interventions. Patients completed the items for this measurement at baseline (T0) and for each quarter thereafter over the 12-month period (T1, T2, T3, and T4).

We based the health outcome measure on the total change in participants' HbA1c values from baseline. HbA1c values were measured on a scale from 1 through to the upper end of 20. A good HbA1c is considered to be below 7 (where > 7 is too high) and above 5 (where < 5 is too low). Values well above 7 are typical for newly diagnosed patients. By measuring the change in HbA1c, we were able to handle patient differences in their initial HbA1c values.

4. Results

We elected to pool our data across time for two reasons. Luo, Baxter, and Taylor (2007) reported that partial least squares (PLS) adjusts for correlated error terms that may result from repeated measures, resulting in the appropriate estimation of the underlying model and error structure. In addition, we pooled data for statistical reasons. As a safeguard, we followed Venkatesh et al.'s (2003) procedure to determine whether pooling data across time was a violation of the assumption of independence. We tested for correlated errors of changes in HbA1c from T0 to T4. All the error correlations, except for one, were not significant.[1] The pooled data resulted in 95 data cases.

Data were analyzed using PLS as implemented by PLS-Graph (Version 3.00; power = .975; see MacCallum, Browne, & Sugawara, 1996). PLS is a regression-based technique that can analyze measurement and structural models simultaneously. We elected to use PLS because it is ideal in the early stages of theory development and places minimal demands on residual distributions (i.e., using bootstrapping, a nonparametric approach, for estimating PLS estimates; see Chin, 1998). PLS-Graph generates loadings for manifest variables and constructs (similar to principal components analysis), standardized regression coefficients between constructs, t-values using bootstrapping, and R2 values for any endogenous constructs.

4.1. Measurement Models

To assess the measurement model, we looked at individual item reliability, convergent validity and internal consistency for constructs that had multiple measures, and discriminant validity for both single and multiple measure item constructs following well-established guidelines. For individual item reliability with multi-item constructs that had more than one measure, we chose items with loadings greater than .707, as this ensures the construct explains more than 50 percent of the variance in the item. We used Fornell and Larcker's (1981) measure to assess internal consistency. Values greater than .7 are generally considered to be indicative of internally consistent scales. For convergent validity, we again used a measure from Fornell and Larcker (1981) known as average variance extracted (AVE). Values greater than .5 are considered adequate for convergent validity. To demonstrate discriminant validity, all items should load higher on their construct than on other constructs in the model (i.e., loadings greater than cross-loadings), and average variance shared between the construct and its items should be greater than the variance shared between this construct and other constructs (Chin, 1998).

All constructs were modeled using reflective indicators. The measurement model was examined to ensure that all manifest variables were psychometrically sound. Based on this analysis, we reexamined the items that performed poorly and modified the scales. A total of five items were dropped at this stage. Two items from the Enabling Technology Factor (measured by the knowledge dimension of the UCQ) were unreliable (i.e., current knowledge of word processing and current knowledge of spreadsheets) because they did not fit the web context of our study. The Predisposing Factor (measured by DSE) had two items that performed poorly (i.e., I could fit exercise into my life, and I could treat a low blood sugar); these items were dropped from the analyses, leaving three items in this scale. Finally, one item in the diabetes self-care behaviors (i.e., if your blood sugar was low [below 4] did you re-treat with 15 grams of fast-acting sugar if your blood sugar was still less than 4) was dropped due to its low loading. This item reflects the most specific aspect of diabetes self-care activities and may have been weaker due to greater variation in respondents' experiences.

Table 2 shows the measures of internal consistency and convergent validity for the refined scales. All scales were internally consistent (internal consistency reliability values > .7) and satisfied the heuristic requirements for convergent validity (AVE values > .5). Discriminant validity was evident because the square roots of the shared variance between the constructs and their measures were higher than the correlations across the constructs (see diagonal of Table 2). The final factor structures for the constructs are presented in Appendix C and confirm discriminant validity because the item loadings were greater than .7 (except for one item in the Enabling Technology factor, which we continued to

[1] Results of the correlated errors test are available from the authors.

include in our analysis due to its relationship to our theoretical model), and lower than the cross-loadings. We concluded that the constructs were psychometrically sound.

Table 2. Measurement Model Estimation

	Mean	Std Dev	# of Items	AVE	ICR	ITP	ITR	ITE	WLU	CSCP	CSCR	CSCE	DSC	A1c
ITP	8.0	1.8	10	.812	.977	**.901**								
ITR	19.0	31.0	1	---	---	-.172	---							
ITE	5.0	1.5	5	.700	.920	.597	.026	**.837**						
WLU	10.5	18.0	1	---	---	.106	.686	.082	---					
CSCP	7.2	1.8	3	.680	.863	.270	.083	.192	.192	**.825**				
CSCR	6.9	1.0	1	---	---	-.065	-.031	-.054	-.012	-.043	---			
CSCE	61.5	23.6	1	---	---	.013	.236	.013	.158	.097	-.241	---		
DSC	1.5	1.0	6	.684	.928	-.199	.011	-.249	-.336	-.341	-.155	.039	**.827**	
A1c	-0.52	1.6	1	---	---	-.019	-.173	-.012	-.430	-.104	.047	-.155	.462	---

Std Dev = Standard Deviation; ICR = Internal Consistency Reliability; AVE = Average Variance Extracted; ITP = Information Technology Predisposing Factors; ITR = Information Technology Reinforcing Factors (Web-based Communication); ITE = Information Technology Enabling Factors; WLU = Web-based Learning Resource Use; CSCP = Chronic Self-Care Predisposing Factors; CSCR = Chronic Self-Care Reinforcing Factors; CSCE = Chronic Self-Care Enabling Factors; DSC = Diabetes Self-Care Management Activities; A1c = Health Outcome.
Note: Diagonal elements in bold are the square root of AVE.

4.2. Structural Model

In order to determine the significance of the path coefficients, PLS estimates the standard error with 500 samples consisting of 95 cases each. The results for the structural model are depicted in Figure 3. We elected to only examine the direct effects of the proposed double adoption of IT use and self-care behaviors using PPM. Despite the lack of correlated errors and the use of PLS, our pooling of the data across the different points of time suggests some caution in interpreting the results, given the possibility of theoretically changing causes and effects for the patients across time.

In the technology adoption sub-model of the antecedents of Web-Based Learning Resource Use, two of the five hypotheses were supported. Stating our conclusions in the confirmatory form by indicating whether a path has a significant association between two constructs, Hypothesis 3 and Hypothesis 4 were supported. Positive paths between Reinforcing Factor of Technology Adoption (i.e., web-based communication between participants and clinicians that was measured by number of chats and e-messages) and Web-Based Learning Resource Use (measured by total number of pages less chats and e-messages accessed per week) ($ß = .742$, $p < .001$) and between Predisposing Factor of Technology Adoption (measured by CSE) and Web-Based Learning Resource Use ($ß = .305$, $p < .01$) were significant.

In terms of the paths from Web-Based Learning Resource Use to the antecedents of Self-Care, Hypotheses 6 and 8, which predicted associations between Web-Based Learning Resource Use and Predisposing Factor for Self-Care (measured by DSE) and between Web-Based Learning Resource Use and Enabling Factors (measured by knowledge scores), were supported ($ß = .192$, $p < .05$; $ß = 0.158$, $p < .05$). Both the paths from Web-Based Learning Resource Use to Diabetes Self-Care Behaviors (measured by self-care questionnaire) (H9a) and from Web-Based Learning Resource Use to Health (measured by change in HbA1c) (H9b) were supported ($ß = .292$, $p < .001$; $ß = -.309$, $p < .001$).

One of the five paths was significant in the Chronic Self-Care Adoption sub-model between the antecedents and self-care behavior. Hypothesis 13, which postulated a relation between Predisposing Factor (measured by DSE) and Diabetes Self-Care Behaviors was significant ($ß = .299$, $p < .001$). In terms of outcomes, Hypothesis 15, which predicted an association between Diabetes Self-Care Behaviors and Health (measured by changes in HbA1c values), was supported ($ß = -.358$, $p < .001$).

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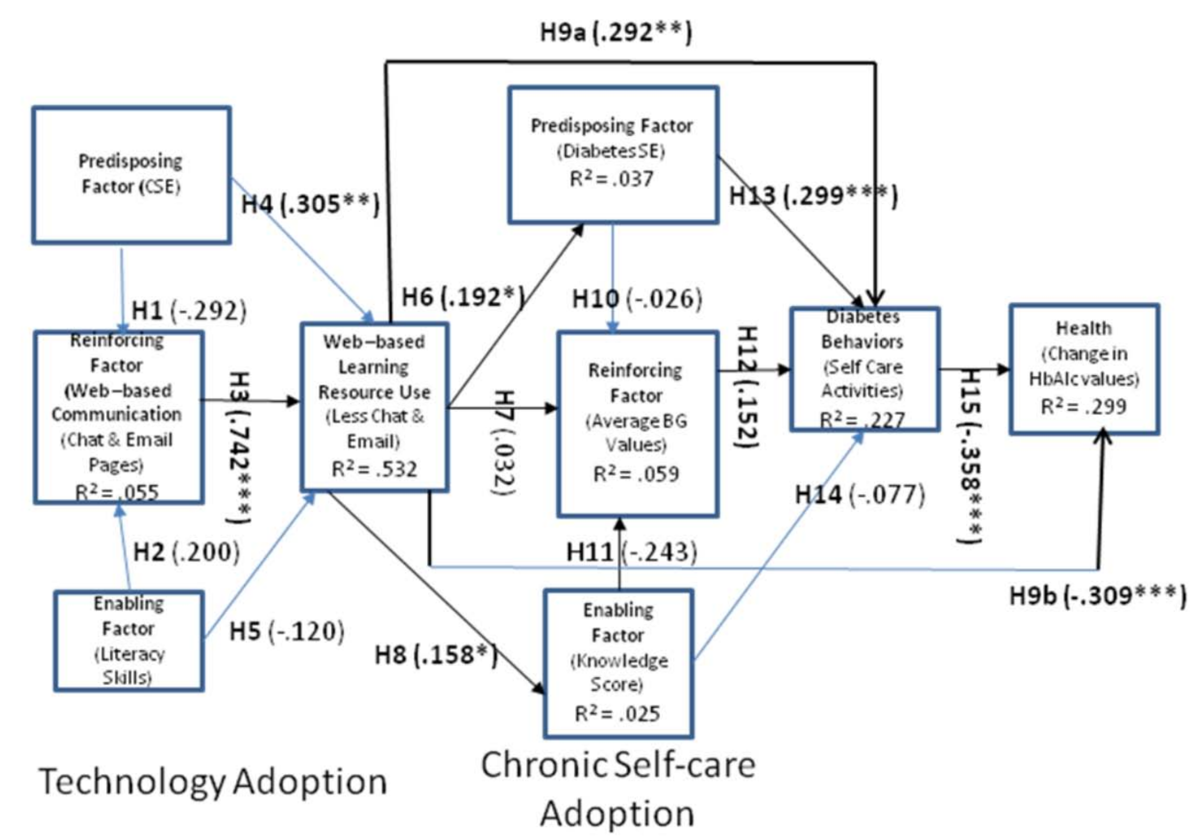

Note: * significant at the 0.05 level (two-tailed); ** significant at the 0.01 level (two-tailed); *** significant at the 0.001 level (two-tailed).

Figure 3. Structural Model of Double Adoption of PPM

Overall, our technology adoption model accounted for only 5.5 percent of explained variance in the Reinforcing Factor of Technology Adoption (Web-Based Communication) and 53.2 percent of the explained variance in Web-Based Learning Resource Use. Within the chronic self-care adoption model, the proposed model accounted for 3.7 percent of the explained variance of Predisposing Factor, 5.9 percent of the explained variance of Reinforcing Factor, 2.5 percent of the explained variance of Enabling Factor, and 22.7 percent of the explained variance in Diabetes Self-Care Behaviors. The proposed model accounted for 29.9 percent of the explained variance in Health (i.e., change in HbA1c values). The amount of variance explained by the proposed model is reasonable, given this is the first test of this theoretical path model in a longitudinal field setting, and given that only one factor of each multi-dimensional category—Predisposing, Reinforcing, and Enabling factors—was investigated.

5. Discussion

Given these findings, our proposed double adoption PPM model was partially supported by the variance explained by the complete model and a number of significant paths throughout the model. The project demonstrates which particular theoretical pathways among the antecedents for use of the eHealth system (technology adoption) and the antecedents for self-care behaviors for newly diagnosed patients with diabetes (chronic self-care adoption) affect changes in HbA1c (health outcomes) and which particular theoretical pathways require additional investigation. With over 29 percent of the variance in changes in HbA1c (i.e., the primary measure of diabetes care) explained through the double adoption model of diabetes self-care activities, the overall result bodes well for the early investigation of how eHealth system use affects the health of a chronic patient population.

Examining how web-based learning resource use affects two out of the three antecedents to self-care, and self-care and health directly, the results suggest that web-based learning resource use affects patient health through all three of these pathways in PPM. Web-based learning resource use increases the self-efficacy of patients (3.7 percent of the variance explained) toward self-care, predisposing them to carry out self-care behaviors (22.7 percent of the variance explained by the endogenous constructs), which affects their health outcomes. Web-based learning resource use also affects self-care behaviors directly, which affects health. Finally, web-based learning resource use affects health directly. This partial mediation of web-based learning resource use suggests that beyond the general measures of self-efficacy toward self-care (i.e., a predisposing factor) and self-care behaviors, there is something more detailed and nuanced going on with patients using eHealth systems that cannot be fully captured through overall measures of these complex meta-categories and behaviors. We suspect this may be due to patients developing specific and tacit knowledge about their own specific condition and the activities that affect their health outcomes. The possibility of tacit knowledge is also supported by the influence of web-based learning resource use on the enabling factors for self-care (measured by knowledge of diabetes self-care). Surprisingly, general knowledge of diabetes self-care appears to be unimportant to the adoption of self-care behaviors associated with changes in HbA1c. Instead, perceptions of self-care efficacy (i.e., a predisposing factor) toward self-care management (the ability to carry them out successfully) suggest that a patient requires specific knowledge and self-efficacious perceptions in order to perform self-care management activities (i.e., diabetes behaviors).

Finally, the chronic self-care pathway also shows that average BG values, a reinforcing factor, do not have a significant influence on self-care activities. This suggests that increased web-based learning resource use is not correlated with average BG values, and these biomedical results do not affect the uptake of self-care behaviors.

Our results also show that over 53.0 percent of the variance in web-based learning resource use is explained by its three antecedents, thus, providing important insight into the PRE factors that are most important to eHealth use. Delving into the path model detail, our results suggest that both the predisposing (i.e., CSE) and reinforcing factors (i.e., web-based communication use of asynchronous and synchronous tools with clinicians) have a strong and significant influence on total web-based learning resource use. The development of CSE and the number of discussions with clinicians about patients' diabetes results appear to be important in influencing overall use of the eHealth system. Thus, the results suggest that reinforcing patient use of eHealth through chat and e-message discussions with clinicians is crucial to patients' overall use of the learning functionalities of eHealth systems. Patients' interactions with clinical personnel appear to be essential to encouraging their use of the learning functionalities of eHealth systems. Previous computer literacy, as an enabling factor for IT use, is not as important in our population of patients as an initial or developing self-efficacy toward eHealth use and the reinforcement of that use by clinician use of the system. Our results, however, must be interpreted cautiously when generalizing to an entire population of patients who may not have the type of access to computers and the Internet as those included in this study.

6. Implications for Research and Practice

There are a number of implications for research arising from our study. For eHealth research, our results support some recent experimental findings that eHealth systems can support diabetes monitoring and self-care (Corriveau et al., 2008; Kim & Jeong, 2007; Kim & Kim, 2008; Kwon et al., 2004). Our individual-level analysis illustrates that patients, especially newly diagnosed ones, need online interaction with clinicians to reinforce eHealth learning use, and that this type of IT use affects the predisposing and enabling factors that influence self-care practices of adoption of chronic self-care behaviors.

For both eHealth and IS research, our double adoption of both eHealth web system and self-care practices using PPM may illustrate a more complete picture of the causal influences from the antecedents of eHealth use to behavior and to health outcomes. Our double adoption approach also provides early evidence of the predisposing factors that affect diabetes self-care and health, which could be cautiously generalized to chronic care conditions. Most of the eHealth research so far has only focused on one part of the causal chain, often using experimental studies to analyze group differences without a particular theory to analytically test eHealth functionality and individual pathways (Dalton, 2008; Sigurdardottir, Jonsdottir, & Benediktsson, 2007). Combining both electronic content and interactive functionality illustrates how important it is to identify the combined advantages and disadvantages of eHealth functionality. Our study, borrowing on the antecedents of IT use from IS research, also addressed a gap in the eHealth literature investigating the antecedents to eHealth learning use. Finally, the future roll-out of an eHealth system can take into account individual variation and decide which functionality can be used by different individuals and how this use may affect self-care behaviors and health outcomes (Azar & Gabbay, 2009; Dalton, 2008; Sigurdardottir et al., 2007).

For IS research, the double adoption model provides early evidence that web-based learning resource use may be influenced by predisposing and reinforcing factors, and that these may make a difference in attaining important outcomes. In our context, web-based learning resource use increases self-care self-efficacy, diabetes knowledge, and self-care practices, as well as decreases HbA1c. Our use of PPM also illustrates a similar, but different theoretical approach to organizing the attitudes, knowledge, and behaviors of IT use into PRE factors (Green & Kreuter, 2005). We have also shown that modeling web-based learning resource use and behaviors as a double adoption method may be worthwhile in the many other IT adoption and acceptance settings.

The individual-level analysis combined with the double adoption method responds to a number of calls in the IS research community to investigate the effects of IT use on other outcomes beyond satisfaction, behavioral intention, and IT use (Fichman, 2004).

Another important implication for IS research from our study of diabetes care is that it illustrates how web-based learning resource use may affect important and substantive dependent variables, such as behavioral and biomedical outcomes related to health. In general, such performance outcomes have been difficult to determine and measure in the more traditional business organizations where IS research is conducted. We hope that an extended focus on the behaviors changed by increased web-based learning resource use may be both motivated and informed by our approach.

There are a number of important practical implications from the study. Our findings provide early evidence that clinicians need to interact with their patients online in order for eHealth to be successful. We also show that an eHealth system may be accessible to people with varying computer knowledge, but not varying CSE. This suggests that technically less-proficient patients may still be able to access eHealth systems, which is important for clinics that elect to adopt eHealth, but it requires the clinics to manage and foster patients' self-efficacy toward system use and not technical proficiency per se.

Finally, our results show that the use of eHealth systems may, on its own or through other pathways, significantly affect chronic self-care behaviors and health outcomes. Knowing that eHealth system use may have considerable impact on people's lives and which pathways work best provides early and important insights into the future design and delivery of eHealth systems.

7. Limitations and Conclusions

Before concluding the paper, we wish to highlight a number of limitations and opportunities for future research arising from them. Typical of cross-sectional data, the correlations could be the result of respondents wishing to be consistent and guessing the researchers' intentions. We have tried to address this problem by measuring patients at numerous points in time and by measuring objective outcomes, such as behaviors (admittedly self-report), web system use, and health results. Future studies that use time lagging of responses and other objective measures of behavior could help in addressing these issues.

Our model also illustrates a number of paths among the traditional factors in IS adoption and acceptance research that are not supported and low variance explained for some of the endogenous constructs. This requires further exploration and research to explain why this population appears to defy conventional theoretical relationships and why our proposed double adoption model provides additional insights into health care behaviors and biomedical outcomes. We have already suggested a few theoretical possibilities. Other possibilities may be difficult with measurements that do not capture the complexity of the theoretical constructs and a small sample size. Green and Kreuter (2005) theorize that PRE factors are meta-categories of factors that influence health-care behaviors and health. Our single-item measures of the reinforcing factors of technology adoption (i.e., communication use of synchronous and asynchronous functionalities) and chronic self-care adoption may not be capturing the complex domains of these important factors. For example, the reinforcing factor of web-based communication use does not include encouragement, physical pain, peer influences, and rewards. This limitation is also applicable to the single-item measure of the reinforcing factor (i.e., average BG values) of chronic self-care adoption and the enabling factors of technology adoption and chronic self-care adoption. Future research focusing on better measurements for the meta-categories of reinforcing factors and enabling factors is required.

Partial support of the paths depicted in the proposed double adoption of PPM and the low variance explained of endogenous constructs may also be attributed to a small sample size and a restricted population of users. Replication of our study with a larger sample size may provide additional support for our proposed model and additional evidence of our findings. More research investigating our proposed double adoption of PPM is needed.

Our study investigates a specific population of people living in a particular time and place and with a specific condition (diabetes) immediately after diagnosis. We confirmed that the characteristics of the patients referred to the BHL program are very similar to the characteristics of the patients not referred to the BHL program. Generally, patients are not referred to BHL program because of a lack of awareness or because the primary physician elects to provide the diabetes education. Care will have to be taken in generalizing and applying the findings wholeheartedly to other research and practical projects as a result. Further investigation with other chronic conditions, beyond diagnosis, and in other populations of people is required. Finally, despite collecting data over 12 months, additional data beyond this time frame is required to determine if patients continue to manage their self-care activities and maintain diabetes control.

Despite these limitations, we believe that our study has shown that IS research may have much to offer eHealth research, and eHealth research may have much to offer IS research. Our combined adoption model of eHealth use and self-care behaviors, leading directly and indirectly to changes in health outcomes, using a well-established theory in the health promotion literature and theories, and using measures from IS appears to jointly inform the two fields. Consequently, the quest for the dependent variable in IS (DeLone & McLean, 1992) may have been identified in one specific way and one specific context, and the use of IS and health promotion theories and measures to address methodological and theoretical issues in eHealth may have been partially addressed (Azar & Gabbay, 2009). We have highlighted many opportunities for future research and practice, which we hope may be informed by our approach. In doing so, we appear to have addressed some of the challenges in eHealth implementation and its impact (Wickramasinghe et al., 2005), and we may have provided some theoretical insight onto an emerging discipline (eHealth) through a well-established one (diffusion of innovations) (Fichman et al., 2008).

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Appendices

Appendix A. Hypotheses

Technology Adoption Hypotheses:

H1: *In an eHealth educational environment, a predisposing IS factor (measured by CSE) will not be associated with a reinforcing factor of web-based communication (number of chats and e-messages).*

H2: *In an eHealth educational environment, an enabling IS factor (measured by Computer Literacy) will not be associated with a reinforcing factor of web-based communication (number of chats and e-messages).*

H3: *In an eHealth educational environment, a reinforcing web-based communication factor (number of chats and e-messages) will not be associated with the use of the web-based learning resource (measured by total web system use minus chats and e-messages).*

H4: *In an eHealth educational environment, a predisposing IS factor (measured by CSE) will not be associated with the use of the web-based learning resource (measured by total web system use minus chats and e-messages).*

H5: *In an eHealth educational environment, an enabling IS factor (measured by literacy skills) will not be associated with the use of the web-based learning resource (measured by total web site use minus chats and e-messages).*

Technology and Chronic Self-Care Adoption and Outcome Hypotheses:

H6: *In an eHealth educational environment, the use of the web-based learning resource (measured by total web system use minus chats and e-messages) will not be associated with a self-care predisposing factor (measured by diabetes self-efficacy).*

H7: *In an eHealth educational environment, the use of the web-based learning resource (measured by total web system use minus chats and e-messages) will not be associated with a self-care reinforcing factor (measured by average blood glucose values in a journal).*

H8: *In an eHealth educational environment, the use of the web-based learning resource (measured by total web system use minus chats and e-messages) will not be associated with a self-care enabling factor (measured by a total knowledge score of self-care practices).*

H9a: *In an eHealth educational environment, web-based learning resource use (measured by total web system use minus chats and e-messages) will not be associated with self-care behaviors (measured by diabetes behaviors self-care activities).*

H9b: *In an eHealth educational environment, the use of the web-based learning resource (measured by total web system use minus chats and e-messages) will not be associated with health (measured by the change in HbA1c values).*

Chronic Self-Care Adoption Hypotheses:

> ***H10:*** *In an eHealth educational environment, a chronic self-care predisposing factor (measured by diabetes self- efficacy) will not be associated with a reinforcing factor (measured by average BG values).*

> ***H11:*** *In an eHealth educational environment, a chronic self-care enabling factor (measured by diabetes knowledge score) will not be associated with a reinforcing factor (measured by the average of BG values).*

> ***H12:*** *In an eHealth educational environment, a chronic self-care reinforcing factor (measured by average Blood Glucose values) will not be associated with self-care behaviors (measured by diabetes behaviors self-care activities).*

> ***H13:*** *In an eHealth educational environment, a chronic self-care predisposing factor (measured by diabetes self-efficacy) will not be associated with self-care behaviors (measured by diabetes behaviors self-care activities).*

> ***H14:*** *In an eHealth educational environment, a chronic self-care enabling factor (measured by knowledge score) will not be associated with self-care behaviors (measured by diabetes behaviors self-care activities).*

Health Outcomes:

> ***H15:*** *In an eHealth educational environment, increases in self-care behaviors (measured by diabetes behaviors self-care activities) will not be associated with health (measured by the drop in HbA1c values).*

Appendix B. Screenshots of eHealth Software

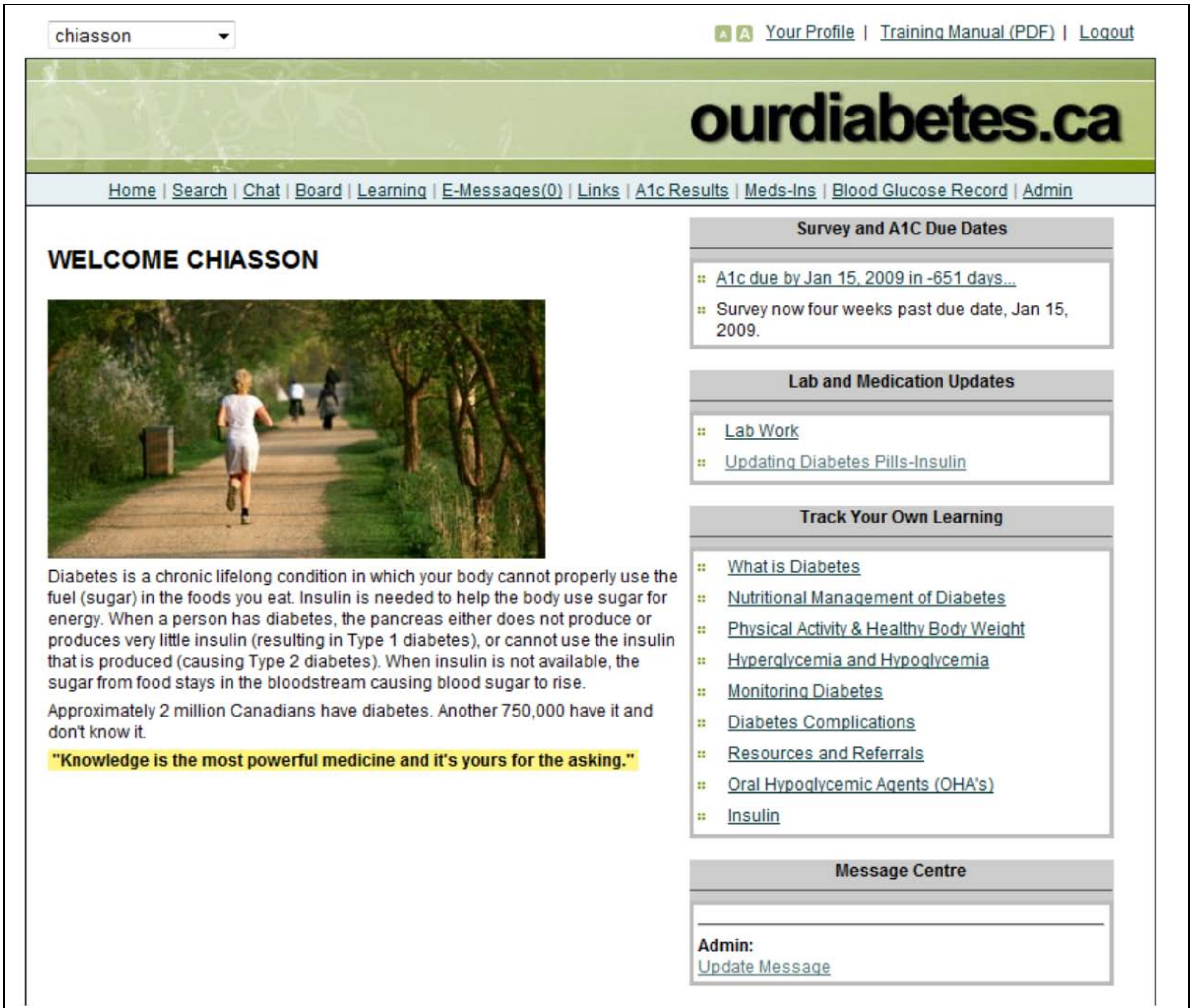

Figure B1. Image of Home Page

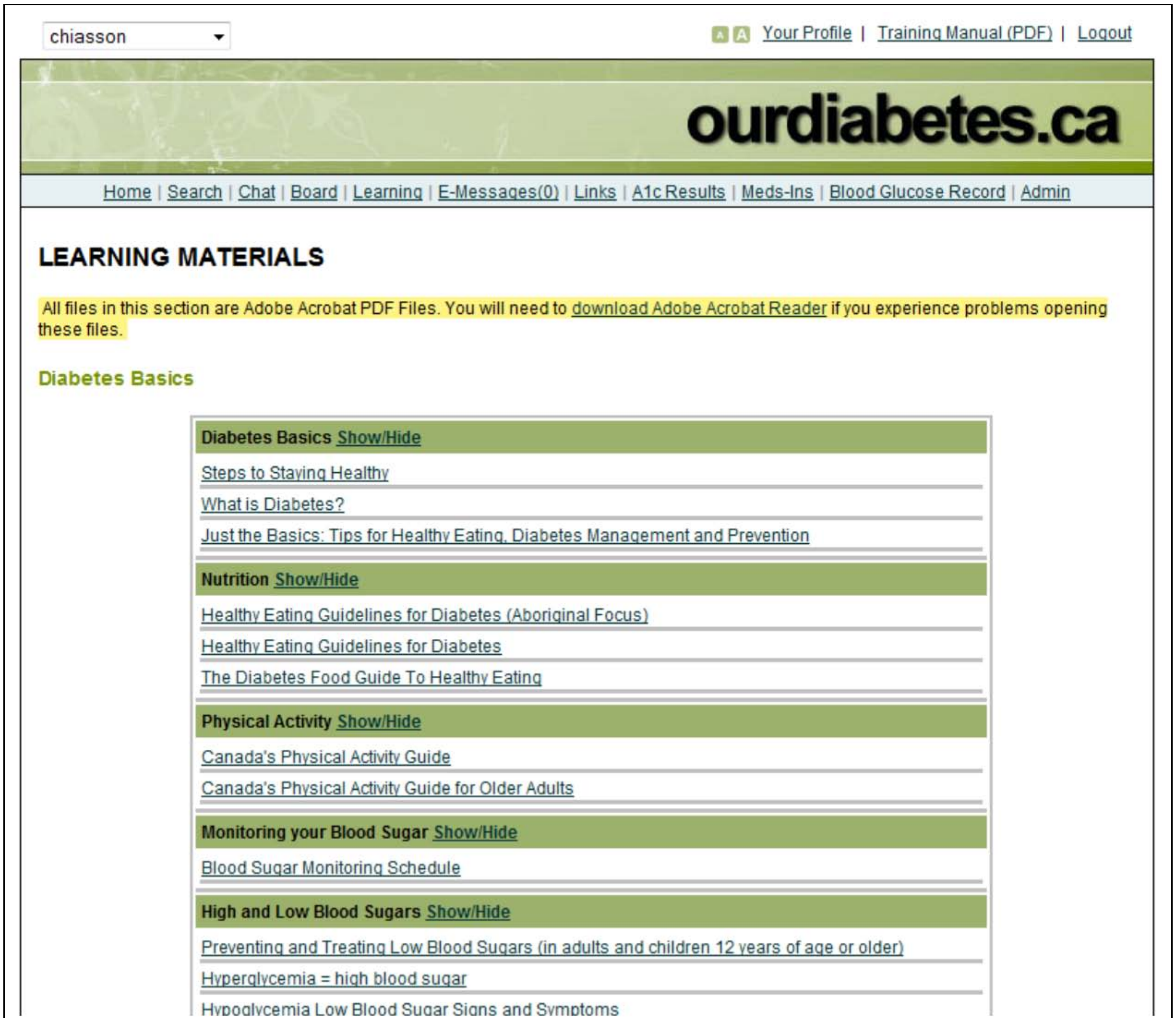

Figure B2. Image of Learning Material Page

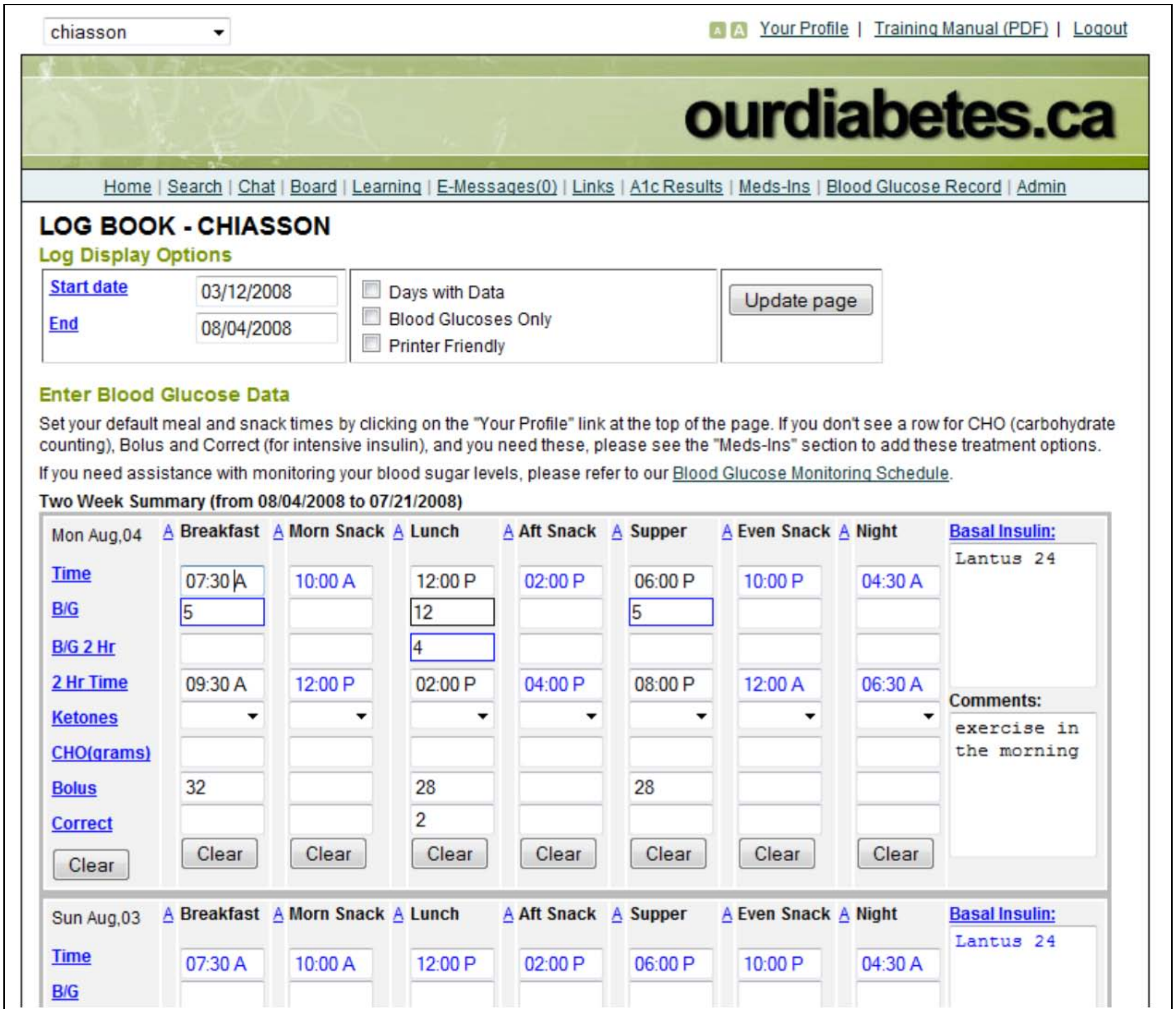

Figure B3. Image of Blood Glucose Journal Page

Appendix C. Partial Least Squares: Measurement Analysis

Table C1. Item Loadings and Cross-Loadings from PLS

Item #	Item	ITP	ITR	ITE	WLU	CSCP	CSCR	CSCE	DSC	A1c
j1	I could use the eHealth web portal if there was no one around to tell me what to do as I go.	**.800`**	-.059	.567	.057	.330	-.097	.031	-.064	.150
j2	I could use the eHealth web portal if I had never used a website like it before.	**.837**	-.083	.556	.153	.296	-.094	.092	-.133	-.085
j3	I could use the eHealth web portal if I had only the site help for reference.	**.854**	-.108	.598	.034	.231	-.059	-.013	-.076	.207
j4	I could use the eHealth web portal if I had seen someone else using it before trying it myself.	**.941**	-.161	.591	.095	.154	-.008	.018	-.153	-.019
j5	I could use the eHealth web portal if I could call someone for help if I got stuck.	**.912**	-.168	.515	.064	.197	-.062	.061	-.178	-.049
j6	I could use the eHealth web portal if someone else had helped me get started.	**.944**	-.178	.565	.114	.238	-.054	-.015	-.270	-.078
j7	I could use the eHealth web portal If I had a lot of time to complete the task using the site.	**.914**	-.273	.429	.073	.243	-.048	-.020	-.213	-.059
j8	I could use the eHealth web portal if I had just the built-in help facility for assistance.	**.944**	-.148	.582	.121	.269	-.003	-.004	-.244	-.050
j9	I could use the eHealth web portal if someone showed me how to do it first.	**.931**	-.141	.586	.087	.265	-.139	-.004	-.147	.026
j10	I could use the eHealth web portal if I had used a similar website before this one to do similar tasks.	**.920**	-.090	.531	.146	.293	-.073	.037	-.180	-.015
Chat/ Email	Number of chats and e-messages (system logs).	-.172	**1.00**	.026	.686	.083	-.031	.236	.011	-.173
a1_3	Describe knowledge of Email.	.538	.024	**.954**	.070	.208	-.053	.000	-.258	.008
A1_4	Describe your current knowledge of Web Browsers.	.470	.035	**.837**	-.009	.076	.006	.000	-.270	-.061
A1_5	Describe your current knowledge of Search Engines.	.525	-.020	**.896**	.040	.201	.021	-.014	-.331	-.021
A1_6	Describe your current knowledge of Bulletin Boards and Message Boards.	.550	.018	**.839**	.069	.129	-.159	.016	-.156	-0.044
A1_7	Describe your current knowledge of Chat Rooms.	.398	-.045	**.618**	-.014	.128	-.249	-.045	-.198	-.059
IT Use	Average of the number of web pages (excluding chats and e-messages) accessed per week (system logs).	.106	.686	.082	**1.00**	.192	-.012	.158	-.336	-.430
i1	I could test my blood glucose regularly.	.180	.071	.082	.242	**.916**	-.030	.073	-.367	-.114

i2	I could follow the healthy eating guidelines for diabetes.	.388	.092	.059	.128	**.817**	.008	.116	-.237	-.061
i3	I could keep my blood glucose at the right level.	.063	.024	.359	-.045	**.731**	-.171	.044	-.137	-.060
BG Average	Average of BG values recorded in BG journal.	-.065	-.031	-.054	-.012	-.043	**1.00**	-.240	-.155	.047
Knowl-edge Score	Percentage of correct answers for 23 multiple-choice questions.	.013	.236	.013	.158	.097	-.241	**1.00**	.039	-.155
f4_1	Did you test your blood sugar at least once a day?	-.090	-.096	-.081	-.383	-.357	.109	.004	**.738**	.340
f4_2	Did you test your blood sugar more than once per day?	-.141	-.042	-.143	-.391	-.283	.103	.049	**.780**	.345
f4_3a	If your blood sugar was low (below 4), did you take 15 grams of fast-acting sugar (i.e., glucose tablets, ½ cup unsweetened apple juice, or ¾ cup unsweetened orange juice)?	-.101	-.009	-.130	-.328	-.317	-.240	.029	**.883**	.345
f4_3b	If your blood sugar was low (below 4), did you re-test your blood sugar in 15 minutes?	-.300	.045	-.318	-.269	-.310	-.238	.001	**.887**	.488
f4_3d	If your blood sugar was low (below 4), did you eat a meal or snack within 1 hour of a low blood sugar?	-.129	.111	-.225	-.099	-.150	-.301	.072	**.852**	.426
f4_3e	If your blood sugars were low, did you do something about it (i.e., make an effort to understand why it happened to prevent it from re-occurring, talk to a health care professional, modify your diet or exercise, etc.)?	-.206	.055	-.346	-.166	-.251	-.189	.051	**.813**	.328
HbA1c	Change in HbA1c values over time (i.e., $T_1 – T_0$; $T_2 – T_0$; $T_3 – T_0$; and $T_4 – T_0$.	-.019	--.073	-.012	-.430	-.104	.047	-.155	.462	**1.00**

Notes: ITP = Information Technology Predisposing Factor—scale anchors range from 1 (Not at all Confident) to 10 (Totally Confident);
ITR = Chats and Email Reinforcing Factor for Web-based Communications;
ITE = Information Technology Enabling Factor—scale anchors range from 0 (No Knowledge) to 7 (Complete Knowledge);
WLU = Web-Based Learning Resource Use;
CSCP = Chronic Self-Care Predisposing Factor—scale anchors from 1 (Not at all Confident) to 10 (Totally Confident).
CSCR = Chronic Self-Care Reinforcing Factor;
CSCE = Chronic Self-Care Enabling Factor;
DSC = Diabetes Self-Care Activities—scale anchors range from 1 (Never) to 5 (Always);
A1c = Change in HbA1c Values;
BG = Blood Glucose;
IT = Information Technology.

About the Authors

Helen M. KELLEY is an Associate Professor of Information Systems in the Faculty of Management at the University of Lethbridge. Her research focuses on the individual user of information and enterprise resource planning technologies, viewed from social cognitive and attributional perspectives. Her current interests investigate understanding what management of organizations can do to enhance individual acceptance and learning about information systems technologies plus eHealth. Her research has been published in *Information Systems Research, Journal of the Association of Information Systems, The Database for Advances in Information Systems,* as well as other journals.

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Danièle PACAUD is Associate Professor of Paediatrics at the University of Calgary and Division Head of Paediatric Endocrinology. She has an active clinical practice in Paediatric Endocrinology and Diabetes. She has been involved in writing the Canadian Diabetes Association Clinical Practice Guidelines since 2000. Her area of research has been the clinical care and clinical outcome of individuals affected by type 1 diabetes. As such, she has worked on the transition of care from Paediatric to adult care, on recognition, impact and treatment of hypoglycemia, assessment of neuropathy in youth with diabetes and on delivery of care models for youth with diabetes.