ADOPTION OF ELECTRONIC PERSONAL HEALTH RECORDS BY CHRONIC DISEASE PATIENTS: INTEGRATING PROTECTION MOTIVATION THEORY AND TASK-TECHNOLOGY FIT

ADOPTION OF ELECTRONIC PERSONAL HEALTH RECORDS BY CHRONIC DISEASE PATIENTS: INTEGRATING PROTECTION MOTIVATION THEORY AND TASK-TECHNOLOGY FIT

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ABSTRACT

With the increasing prevalence of chronic disease throughout the world, electronic Personal Health Records (ePHRs) have been suggested as a way to improve chronic disease self-management. However, ePHRs are not yet widely used by consumers. Protection Motivation Theory (PMT) has been successfully used to explain health related behaviours among chronic disease patients. In addition, Information Systems (IS) theories such as Task Technology Fit (TTF) have been successfully used to explain information technology adoption. This study combines PMT with Perceived Task Technology Fit (PTTF) and the health self-management readiness concept of the Patient Activation Measure (PAM) to propose a research model which will aid in the understanding of ePHR adoption by chronic disease patients. The role of educational interventions on various elements of the proposed model is also examined. A survey-based study of 230 participants is used to empirically validate the proposed model via structural equation modeling techniques. Results reveal that the PMT constructs, as well as PTTF and PAM all have significant direct or indirect effects on the intention to adopt an ePHR. In addition, the educational intervention analysis indicates that the provision of advanced ePHR education positively influences various constructs in the model, while the use of fear appeals through Diabetes complication education does not have an effect.

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Glossary of Terms

Acronym	Full Name
ADOPT	PHR Adoption Intention
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
CMB	Common Method Bias
DC	Diabetes Complications
DEC	Diabetes Education Centre
EHR	Electronic Health Record
EI	Educational Intervention
EMR	Electronic Medical Record
ePHR	Electronic Personal Health Record
FITT	Fit between Individual, Task and Technology
IS	Information Systems
IT	Information Technology
MANOVA	Multivariate Analysis of Variance
OPMT	Ordered Protection Motivation Theory
PAM	Patient Activation Measure
PEOU	Perceived Ease of Use
PHR	Personal Health Record
PLS	Partial Least Squares
PMT	Protection Motivation Theory
PTTF	Perceived Task Technology Fit
PU	Perceived Usefulness
RC	Response Costs
RE	Response Efficacy
SE	Self-Efficacy
SEV	Severity
SEM	Structural Equation Modeling
TAM/TAM3	Technology Acceptance Model/Technology Acceptance Model v3
TPB	Theory of Planned Behaviour
TTF	Task Technology Fit
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
VUL	Vulnerability
WHO	World Health Organization

Chapter 1. Introduction

This research integrates theory from health behaviour and Information Systems domains in an endeavour to understand the adoption intention of a consumer health information technology. Specifically, this research examines the intention to adopt electronic Personal Health Records (ePHRs) amongst people with Type 2 Diabetes for the self-management of their chronic disease. The worldwide incidence of chronic disease and Type 2 Diabetes is growing, and the impacts of these diseases will affect a great number of the world's population (Alwan, et al., 2010; Alwan, et al., 2011; World Health Organization, 2005; 2013a). The self-management of chronic diseases such as Type 2 Diabetes involves a set of complex and time consuming tasks. ePHRs can aid people with Type 2 Diabetes in the self-management of their condition, yet the adoption of ePHRs has been slow, and previous research has produced mixed results in understanding the factors involved in the adoption of this technology. Therefore this research takes a new approach in investigating the adoption of ePHRs, through the combination of Protection Motivation Theory (PMT) and the Patient Activation Measure (PAM) from the health care domain and Task-Technology Fit (TTF) from the Information Systems (IS) domain, and explores the impact these theories and concepts have on the intention to adopt an ePHR for the self-management of a chronic disease.

1.1. Need for this Research

The World Health Organization's (WHO) published statistics on chronic disease reveal staggering effects on morbidity, mortality and economic costs to society (Alwan, et al., 2011; World Health Organization, 2005). Reports indicate that chronic non-communicable disease[1] is the leading cause of death worldwide, with over 36 million people worldwide dying in 2008 from chronic disease and its associated complications. However it is estimated that over 9 million of these chronic disease deaths could have been prevented (Alwan, et al., 2011). Estimates show that Diabetes accounted for

[1] Note: for the remainder of this document this class of diseases is referred to as chronic disease.

approximately 1.3 million of the chronic disease deaths (Alwan, et al., 2011), and projections indicate that Diabetes will be the seventh leading cause of death worldwide by 2030 (Alwan, et al., 2010).

Self-management of a chronic disease is defined as "the person with the chronic disease engaging in activities that protect and promote health, monitoring and managing the symptoms and signs of illness, managing the impact of illness on functioning, emotions and interpersonal relationships and adhering to treatment regimes." (Victoria Department of Health, 2007). For chronic diseases such as Diabetes, "self-management practices have substantial consequences on morbidity and mortality" (Heisler, et al., 2002, p. 243). Studies have shown the health and well-being improvements (both physical and mental) that can occur due to effective chronic disease self-management (Bodenheimer, et al., 2002; Chodosh, et al., 2005; Lorig, et al., 2001; Lorig, et al., 1999; Warsi, et al., 2004). However, the self-management of a chronic disease such as Type 2 Diabetes involves a set of complex, time consuming tasks that can overwhelm individuals who suffer from this condition (Russell, et al., 2005).

Electronic Personal Health Records (ePHRs), a form of Consumer Health Information Technology have been proposed as a way to assist chronic disease patients in self-managing their disease (Assadi & Hassanein, 2009; Tang, et al., 2006). While all patients can potentially benefit from the adoption of ePHRs, those patients with chronic conditions can potentially achieve greater benefits due to the increased need to record and access their health related information on a regular basis and the requirement to actively self-manage their disease in a joint effort with physicians and other caregivers (Pope, et al., 2006). It has been shown that patients have limited knowledge of the functionalities and capabilities of ePHRs, and the adoption of ePHRs has been an issue (Assadi & Hassanein, 2009). Consumer Health Information Technologies have been shown to help patients with self-management. However, they can only do so if they are adopted (Or & Karsh, 2009), thus "[Consumer Health Information Technology] system developers and those who implement the systems should pay attention to the underlying reasons and motives for patient acceptance of the [Consumer Health Information] technology" (Or & Karsh, 2009, p. 556). This research examines these underlying reasons and motives in the adoption of ePHRs for Type 2 Diabetes self-management.

1.2. Theoretical Influences

Protection Motivation Theory (PMT) has been used for decades to analyze and predict health related behaviours (Norman, et al., 2005), with meta-analyses showing PMT variables as good predictors of health related behaviours and behavioural intention in general (Floyd, et al., 2000; Milne, et al., 2000). PMT is therefore very appropriate to the health behaviour context of this research study. A variation of PMT, specifically Ordered Protection Motivation Theory (OPMT) has been suggested as an alternative to the traditional PMT (Tanner Jr., et al., 1991). In OPMT, the same variables as PMT are present, however it is proposed that individuals assess the situational threat before they assess the available coping strategies, which then lead to protection motivation, which can be measured as behavioural intentions (Plotnikoff & Trinh, 2010; Tanner Jr., et al., 1991).

Information Systems (IS) theories such as Task-Technology Fit (TTF) have successfully shown the relationships among the variables that can predict consumers' behaviours towards information technology (Goodhue, 1995), specifically examining the fit between the task and the technology. TTF is well suited for this research study, as this study proposes to examine the adoption of ePHR technology for the task of self-management by chronic disease patients (i.e., does the ePHR technology fit the task of chronic disease self-management). TTF in combination with the Technology Acceptance Model (TAM) has been previously shown to provide greater explanatory power than either model alone (Dishaw & Strong, 1999; Klopping & McKinney, 2004). However, this study combines TTF with OPMT, as the OPMT constructs encompass the most salient items from TAM (i.e., Response Efficacy is comparable to Perceived Usefulness, Self-Efficacy is comparable to Perceived Ease of Use, Protection Motivation is comparable to Behavioural Intention to Use) that are critical to this study, but OPMT focuses on health related intentions and behaviours. To date a limited number of studies have combined PMT or OPMT with IS theory. A recent appeal was made for Consumer Health Information Technology acceptance research to incorporate technology acceptance theories (Or & Karsh, 2009). By combining OPMT with TTF, this research is an answer to that call.

Given the voluntary nature of ePHR adoption and usage for the task of chronic disease self-management, it is necessary to examine not only the fit between the task and technology and the technology and the individual (through the lens of TTF), but also the fit between the task and the individual. In this study, the technology is an ePHR, the individual is a person who suffers from Type 2 Diabetes, and the task is Type 2 Diabetes self-management. Therefore, the theoretical concept of the Patient Activation Measure (PAM) was incorporated. PAM assesses an individual's (typically a chronic disease sufferer) readiness for the task of health related self-management (Hibbard, et al., 2005; Hibbard, et al., 2004). In this research, PAM is used to assess the fit between the individual (i.e., a person with Type 2 Diabetes) and the task of Type 2 Diabetes self-management, completing the triangular concept of the fit between all elements of TTF (i.e., task, technology, individual). To the best of my knowledge, this is the first known study to use PAM to address the element of fit between the task and the individual.

Educational interventions have been successfully applied to chronic disease conditions such as asthma and Diabetes (Guevara, et al., 2003; Sigurdardottir, et al., 2007) to bring about behavioural changes. More specifically, self-management educational intervention programs can be of assistance to chronically ill patients (Warsi, et al., 2004). Improving people's understanding of their chronic condition and the tasks involved in self-management has been identified as a key objective in improving the health of chronic disease patients (Pope, et al., 2006). Improving an individual's understanding of his/her chronic condition and the task of self-management can be accomplished through education. Thus, this study also explores the impact of educational interventions on the various factors that influence ePHR adoption for chronic disease self-management. To date, no known studies have applied educational interventions to Consumer Health Information Technology (such as ePHR) adoption studies.

1.3. Research Objectives

The overarching objective of this research is to develop and test a research model that combines OPMT with TTF and PAM, specifically in the context of ePHR adoption by Type 2 Diabetes patients for the purposes of self-management. The main research objectives are as follows:

1. *To investigate and understand the influence of protection motivation theory (PMT) behavioural factors on the adoption of ePHRs by chronic disease patients.*
2. *To understand how the fit between chronic disease self-management task requirements, ePHR technology functionalities and individual characteristics influence the adoption of ePHRs through the lens of Task Technology Fit (TTF) and Patient Activation Measure (PAM).*

In addition to these main objectives, this research also involves the following secondary objectives:

3. *To understand the role Diabetes Complication (DC) and ePHR educational interventions may have on various constructs in the research model.*
4. *To study the effects individual factors (e.g., demographic, socio-economic, health condition, etc.) may have on various constructs in the research model.*

1.4. Document Organization

The remainder of this dissertation document is organized as follows. Chapter 2 provides the contextual background needed to understand chronic disease (including Type 2 Diabetes), self-management and ePHRs. Chapter 3 provides the theoretical background for this research, specifically PMT/OPMT, TTF, PAM and educational interventions. Chapter 4 details the research model and hypotheses which will be tested via the research methodology outlined in Chapter 5. Chapter 6 provides the data analysis of the measurement and structural model, as well as post-hoc analyses. Chapter 7 provides a discussion of the key findings, contributions of this research to academics, practitioners and society, limitations of this research and planned future work in this area.

Chapter 2. Contextual Background

The importance of context in any research study cannot be overlooked. Johns (2006) stressed this in his Academy of Management Review paper by stating "the impact of context on organizational behavior is not sufficiently recognized or appreciated by researchers" (p. 386). He further states that "contextualization can inform hypothesis development, site selection, measurement choice, data analysis and interpretation, and the reportage of research" (p. 386). Therefore this research study strives to take into account the facets and importance of context. Specifically, the context of this study involves chronic disease patients and their adoption of ePHRs for the self-management of their disease. Each of these contextual facets is explained below.

2.1. Chronic Disease and Diabetes

Worldwide, the most prevalent chronic diseases include Diabetes (Type 1 and 2), respiratory disease (e.g., asthma), arthritis, cardiovascular disease (e.g., hypertension) and cancer. The World Health Organization (WHO) estimated that in 2008 (the most recent WHO statistics available), approximately 208,200 Canadians died from chronic diseases, which represented 89% of all deaths in Canada. In the Americas, the number of deaths due to chronic disease totalled over 4.8 million, or 78% of all deaths. The statistics are similar in Europe, where over 8.4 million people died from chronic disease, or 86% of all deaths (Alwan, et al., 2010; Alwan, et al., 2011; World Health Organization, 2005). Globally, deaths from chronic diseases are expected to increase 15% between 2010 and 2020, with increases as high as 20% in some parts of the world (Alwan, et al., 2010). The WHO also reports that worldwide, the population demographic is aging, with nearly every country reporting that the proportion of the population over 60 is growing faster than other age groups (World Health Organization, 2012b). Estimates show that by the year 2050, the proportion of the population over the age of 60 years will have grown to 22%, up from 11% in the year 2000 (World Health Organization, 2012a). The WHO reports that 75% of deaths from chronic disease occur in people over the age of 60 (World Health Organization, 2013b). From a Diabetes perspective, the number of older people (ages 65+) in the United States

diagnosed with Diabetes is over 12 times higher than the number of younger people (aged 45 and under) who are diagnosed with Diabetes (U.S. Department of Health and Human Services Centre for Disease Control, 2013). In another study, it was noted that over 100 million people in the United States suffer from chronic diseases, with an estimated $650 billion spent each year in managing chronic diseases (Warsi, et al., 2004). What is clear from the preceding statistics and also those detailed below in Table 1 are the staggering costs in morbidity and mortality, particularly for the elderly, as well as the economic costs of chronic disease.

Table 1 – Chronic Disease Statistics

	Canada	Americas	Europe	World
Chronic disease deaths, 2005 (2008 for Canada)	208,200	4,823,000	8,414,000	36 million
Percentage of deaths due to chronic disease, 2005 (2008 for Canada)	89%	78%	86%	60%
Projected deaths from chronic disease 2005-2015	> 2 million	53 million	88 million	N/A
Increase in deaths from chronic disease, 2005-2015	15%	17%	4%	N/A
Increase in Diabetes deaths, 2005-2015	44%	80%	23%	N/A
Economic costs of chronic disease, 2005	$500 million	N/A	N/A	N/A
Estimated costs of chronic disease, 2005-2015	$9 billion	N/A	N/A	N/A
Number of lives saved 2005-2015 from a 2% annual reduction in chronic disease death rates	N/A	5 million	8 million	N/A
Economic savings 2005-2015 from a 2% annual reduction in chronic disease death rates	$1 billion	N/A	N/A	N/A

N/A indicates information not available.
(Sources: Alwan, et al., 2011; World Health Organization, 2005)

Diabetes is "a chronic disease that occurs either when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood sugar. Hyperglycaemia, or raised blood sugar, is a common effect of uncontrolled Diabetes and over time leads to serious damage to many of the body's systems, especially the nerves and blood vessels." (World Health Organization, 2013a). It is estimated that 347 million people worldwide have Diabetes, with Diabetes projected to be the seventh leading cause of death worldwide by the year 2030 (World Health Organization, 2013a). There are two different types of Diabetes, Type 1 (formerly called Juvenile, insulin-dependent or child-onset) and Type 2 Diabetes (formerly called adult-onset or non-insulin

dependent). Type 1 Diabetes is characterized by the body's inability to produce insulin, and at this time, there is no known way to prevent or cure the disease (World Health Organization, 2013a). Type 2 Diabetes, which comprises approximately 90% of the incidence of Diabetes, is characterized by the body's ineffective use of the insulin it produces (World Health Organization, 2013a). Both types of Diabetes can cause serious health complications, many of which are outlined in Appendix A, Part 2. It is estimated that people with Diabetes require two to three times the health care resources (compared to people without Diabetes), and Diabetes accounts for up to 15% of some countries' health care budget (Alwan, et al., 2010).

2.2. Chronic Disease Self-Management

The task of chronic disease self-management is of utmost importance to this study. Self-management, an idea that has been around for centuries can be defined as "the systematic application of principles of behaviour to direct a change in one's own behaviour" (Kahn, 1976, p. 178). General self-management has been categorized into the four "M" tasks of self-monitoring, self-measurement, self-mediation and self-maintenance (Kahn, 1976), all of which are applicable to chronic disease self-management. A recent paper specific to Diabetes self-management also utilized a four "M's" approach, dividing Diabetes self-management into the four primary tasks of meal planning, motion (i.e., exercise), medication and monitoring (Darbishire, et al., 2009). What is clear from these categorizations is the variety of complex tasks involved and the effort that must be devoted to perform chronic disease self-management. Thus this study examines the potential for ePHRs to assist in chronic disease self-management tasks.

For participants to consider adopting an ePHR for self-management, there should be evidence that self-management can actually improve their health condition. Self-management is different than traditional patient instruction, in that self-management involves "problem solving skills…a central concept in self-management is self-efficacy – confidence to carry out behavior necessary to reach a desired goal" (Bodenheimer, et al., 2002, p. 2469). A number of studies have shown the positive effects

of self-management for chronic disease patients. Bodenheimer et al. (2002) found that "programs teaching self-management skills are more effective than information-only patient education in improving clinical outcomes" (Bodenheimer, et al., 2002, p. 2469). Lorig et al. (2001; 1999) found that at the six month and two year time-frame, chronic disease patients who practiced self-management exhibited improvements in areas such as exercise, self-reported health, number of hospitalizations, health distress and perceived self-efficacy. Of extreme importance to this study, two separate meta-analyses (Chodosh, et al., 2005; Warsi, et al., 2004) found improvements in Diabetes patient's clinical results for those involved in self-management programs. These studies found statistically and clinically significant reductions in H_bA_{1C} (a blood glucose reading) (Chodosh, et al., 2005) and reductions in both H_bA_{1C} and systolic blood pressure (Warsi, et al., 2004). Both of these studies concluded that self-management programs for people with Diabetes produce important benefits.

It has been estimated that approximately two hours per day are required for Type 2 Diabetes self-management, with 17 distinct tasks (e.g., home glucose monitoring, record keeping, taking oral medication, foot care, oral hygiene, flossing, problem solving, meal planning, shopping, preparing meals, exercise) identified as part of the recommended care for Type 2 Diabetes (Russell, et al., 2005). The time commitment is even higher for those individuals who are newly diagnosed (24% - 35% more time) and/or those who are elderly or infirm (up to twice as much time) (Russell, et al., 2005). Therefore it can be concluded that while Type 2 Diabetes self-management is important, the time commitment required to perform the multitude of complex tasks may be far too arduous for many people who suffer from this chronic disease.

2.3. Electronic Personal Health Records (ePHRs)

Personal Health Records (PHRs) are defined as a "record of an individual's health information by which the individual controls access to the information and may have the ability to manage, track, and participate in his or her own health care…PHRs universally focus on providing individuals with the ability to manage their health information and to control, to varying extents, who can access that health

information. PHRs have the potential to provide individuals with a way to create a longitudinal health history and may include common information such as medical diagnoses, medications, and test results." (U.S. Department of Health and Human Services Office for Civil Rights, 2008). PHRs are however, not just a record of information, but rather the combination of the recorded information with the functionalities that can be used in conjunction with the record for health self-management activities. PHRs are distinctly different from either an Electronic Health Record (EHR) or Electronic Medical Record (EMR), in that PHRs are controlled and maintained by the patient (whereas EHRs and EMRs are controlled and maintained by physicians and hospitals respectively). PHRs can be paper based, or Internet/computer based electronic records (Assadi & Hassanein, 2009; Pope, et al., 2006). In addition, ePHRs (electronic personal health records) can be categorized as i) stand-alone (i.e., patients populate ePHRs with their own data, ePHRs typically reside on patient computers); ii) tethered (i.e., ePHRs are linked to an EHR or other medical information system, so patients can typically view medical EHR information but control by the patient is limited); or, iii) integrated (i.e., patients maintain/control ePHRs, ePHRs have access to multiple medical information systems such laboratory results, etc.) For the purposes of this study, PHRs are considered to be electronic (i.e., ePHRs) and integrated, and therefore ePHRs are defined as electronic records of health-related information that draw from multiple sources while being managed and controlled by the individual. (National Alliance for Health Information Technology, as cited in Kahn, et al., 2009). Estimates indicate that nearly half of the consumers in the United States are still unaware of ePHRs (Whetstone & Goldsmith, 2008), and according to a Deloitte 2008 Survey of Health Consumers, over 60% of respondents would like online access (i.e., electronic) to their medical records (Kahn, et al., 2009). The United States Government called for electronic health records to be available for each individual by 2014 (Richards, 2012), which at this time does not appear to be likely given that only 7% of adults in the United States use an ePHR (Archer, et al., 2011).

Benefits of PHRs/ePHRs include reduced medical errors, better patient quality of care, higher reliability of information provided to health care practitioners, health reminders and education (Sensmeier, 2010), secure online access, comprehensive personal health history, means to become own

health advocate, benchmarks and prompts for maintenance, fluid provider communication, automatic data entry (Randeree, 2009), behaviour changes, connection of individuals through social networks (Kahn, et al., 2009), and improved disease self-management (Assadi & Hassanein, 2009). All patients can potentially benefit from the adoption and use of PHRs/ePHRs, but those patients who are older (or people caring for the elderly) and/or with chronic conditions can achieve higher benefits due to the greater need to access health related information and the requirement to actively manage the chronic disease (Archer, et al., 2011; Logue & Effken, 2012; Pope, et al., 2006; Whetstone & Goldsmith, 2009). These individuals also typically tend to have the most interest in PHR/ePHRs (Archer, et al., 2011). In addition, for chronic care patients, as medical monitoring devices such as glucometers (i.e., a blood sugar measurement instrument) become integrated with computers and the Internet, patients can benefit by having the readings automatically uploaded to their ePHRs (Sensmeier, 2010). One expert indicates that PHRs/ePHRs "may be the quickest path to the fulfillment of [chronic] disease management" (Pope, et al., 2006, pg. 24).

Unfortunately the knowledge of, demand for, and the understanding of the benefits provided by ePHRs are not fully understood by patients, physicians and other stakeholders, and as such the adoption of ePHRs has been an issue (Assadi & Hassanein, 2009; Logue & Effken, 2012). While interest in ePHR technology exists, adoption has been slow (Logue & Effken, 2012). Due to the fact that ePHRs are currently in early stages of development, implementation and adoption trends are vague (Whetstone & Goldsmith, 2009). As stated in Whetstone & Goldsmith (2009), "The few studies of PHR adoption found in the literature demonstrate mixed interest and use. While [some] found favourable attitudes toward PHRs after use, [others] found little interest in PHRs… These studies provide insight into current usage of PHRs, but do not provide insight into motivations for adoption." (pp. 10-11)

An examination of the PHR/ePHR adoption and use studies listed in the Archer et al. (2011) systematic review of PHR/ePHR adoption papers, as well as PHR/ePHR adoption studies published after the Archer et al. (2011) review revealed a limited number of these studies to be theoretical, empirical studies of the drivers/motivations for PHR/ePHR adoption. Rather, most studies were noted to be

descriptive, qualitative, or observational studies that examined PHR/ePHRs from a physician perspective, examined how currently adopted PHR/ePHRs were actually being used, and what these PHR/ePHRs were being used for. The limited number of prior theoretical, empirical PHR/ePHR adoption studies have focused on the use of TAM or individual constructs from TAM (Davis, 2007; Jian, et al., 2012; Morton, 2011; Richards, 2012; Whetstone & Goldsmith, 2009) and/or the theory of planned behaviour (TPB) (Jian, et al., 2012), Unified Theory of Acceptance and Use of Technology (UTAUT) (Randeree, 2009, a Research in Progress Paper), and information boundary theory (Richards, 2012). A summary of all known PHR/ePHR studies that examined motivations for PHR/ePHR adoption (i.e., both the studies in Archer et al. (2011) and those published after) is included in Table 2.

Table 2 – PHR/ePHR Adoption Study Summary

Reference	Title	Theory/Model/ Methodology Used	Findings
(Angst & Agarwal, 2009)	Adoption of Electronic Health Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion	Elaboration Likelihood Model	Study integrated an individual's concern for information privacy with the elaboration likelihood model to examine likelihood of opting-in to an ePHR system and proposed that likelihood of ePHR adoption is driven by concern for information privacy and attitude. Findings from the study revealed that an individual's concern for information privacy interacts with argument framing and issue involvement to affect attitudes toward the use of ePHRs and that attitude toward ePHR use and concern for information privacy directly influence opt-in behavioral intentions.
(Walker, et al., 2009)	Insights for Internists: "I Want the Computer to Know Who I Am"	N/A	People want ePHRs to bring them customized health information and advice and want full and unconstrained access to their health record. In addition, especially for the chronically and acutely ill, privacy is of far less concern.
(Winkelman, et al., 2005)	Patient-Perceived Usefulness of Online Electronic Medical Records: Employing Grounded Theory in the Development of Information and Communication Technologies for Use by Patients Living with Chronic Illness	Grounded Theory	Four themes were discovered that comprise a theoretical framework of patient-perceived information and communication technology usefulness: i) promotion of a sense of illness ownership; ii) patient-driven communication; iii) personalized support; and, iv) mutual trust.

(Zickmund, et al., 2008)	Interest in the Use of Computerized Patient Portals: Role of the Provider–Patient Relationship	Elements of TAM	Motivating persons to use ePHRs may require patient-based adaptations which could include ease of use, direct provider e-mail, and reassurances that access and patient-physician relationships will not be lost.
(Weitzman, et al., 2009)	Acceptability of a Personally Controlled Health Record in a Community-Based Setting: Implications for Policy and Design	N/A	Low levels of awareness and high expectations for PHR/ePHRs are potentially problematic for adoption/use. Educational and technical assistance may be required for new users, especially among older persons. Inadequate health and technology literacy, clarification of responsibility for ensuring accuracy and integrity of health information across distributed data systems, and understanding confidentiality and privacy risks are important in adoption and use. Continued demonstration and evaluation of PHR/ePHRs is essential to advancing use.
(Ross, et al., 2005)	Expectations of Patients and Physicians Regarding Patient-Accessible Medical Records	N/A	Primary determinants of ePHR adoption are not age, race, or education level but rather previous experience with the Internet and patients expectations of ePHR benefits and drawbacks.
(Halamka, et al., 2008)	Early Experiences with Personal Health Records	N/A	ePHRs which share data among patients and providers can achieve successful adoption but require attention to policy regarding privacy, security, data stewardship, and personal control.
(Lafky & Horan, 2008)	Prospective Personal Health Record Use Among Different User Groups: Results of a Multi-wave Study	N/A	Prospective users with disabilities differ from others in their PHR/ePHR preferences. A motivating factor for PHR/ePHR adoption amongst disabled persons is the way in which a PHR/ePHR will work when emergency services are required.
(Ralston, et al., 2006)	Use and Satisfaction of a Patient Web Portal with a Shared Medical Record between Patients and Providers	N/A	Use and satisfaction with ePHR were greatest for services most actively part of clinical care and patient-provider communication. Integration of portal services with clinical care and Electronic Medical Record may be important in meeting the ePHR needs of patients.
(Kim, et al., 2009)	Challenges to Using an Electronic Personal Health Record by a Low-Income Elderly Population	N/A	Findings suggest that those who can benefit the most (i.e., the elderly) from an ePHR system may be the least able to use it. Inability to use the ePHR system was associated with poor computer and Internet skills, technophobia, low health literacy, and limited physical/cognitive abilities.

(Zulman, et al., 2011)	Patient Interest in Sharing Personal Health Record Information	N/A	ePHR systems should explore secure mechanisms for sharing access to the ePHR to improve information exchange among patients and the many persons involved in their health care.
(Logue & Effken, 2012)	Validating the personal health records adoption model using a modified e-Delphi	e-Delphi	Study used e-Delphi methodology to examine the factors involved in adoption or use of an ePHR. Factors were categorized as personal, environmental, technology or chronic disease. These factors operate "concurrently as barriers and/or facilitators to the adoption of PHRs among the older adult with long-term illness. These five main concepts cannot be isolated because individuals commonly weigh risk with benefit in the context of their perceived reality and determine their own personal value for adopting PHRs."(p. 694)
(Jian, et al., 2012)	Factors influencing consumer adoption of USB-based Personal Health Records in Taiwan	Elements of TAM, TPB	Multivariate logistical regression found support for Usage Intention, Perceived Usefulness and Subjective Norm as key factors affecting adoption of ePHRs.
(Davis, 2007)	Acceptance of personal health record technology: A survey analysis of the elderly	TAM	This PhD dissertation used both quantitative and qualitative methods to examine the acceptance of ePHRs amongst the elderly, through the lens of the Technology Acceptance Model. Study found that the elderly population is strongly willing to accept ePHRs, and to encourage adoption, developers need to make ePHRs are secure and accessible to all, and link information between care providers.
(Whetstone & Goldsmith, 2009)	Factors influencing intention to use personal health records	Elements of TAM	Study examined the intention to use ePHRs via the constructs of Personal Innovativeness, Perceived Usefulness and Security/Privacy Confidence. Results showed that all three of these factors were significantly positively related to intention to use an ePHR.
(Morton, 2011)	Examining Acceptance of an Integrated Personal Health Record (PHR)	Elements of TAM	This PhD dissertation revealed people with diabetes showed intentions to use an ePHR, perceive an ePHR is/could become easy to use, and believe an ePHR is useful for self-managing their care and diabetes. ePHR adoption could be improved by continued and more prominent promotion of ePHRs while addressing access and computer/ePHR literacy and ease of use needs among potential adopters.

(Richards, 2012)	A Study of the Intent to Fully Utilize Electronic Personal Health Records in the Context of Privacy and Trust.	TAM, Information Boundary Theory	This PhD dissertation used the technology acceptance model, information boundary theory model and a trust model to examine ePHR usage intentions. "Results indicate that healthcare consumers feel there is a perceived usefulness of ePHR; however they may not see [an] ePHR as easy to use. Results also indicate that the perceived usefulness of utilizing [an] ePHR does not overcome the low perceived ease of use to the extent that healthcare consumers intend to utilize [an] ePHR. In addition, healthcare consumers may not understand the different components of usage: access, management, sharing and facilitating third-party ePHR. Also, demographics, computer self-efficacy, personal innovativeness, healthcare need and healthcare literacy impact a consumer's privacy concerns and trusting intentions in the context of ePHR and intent to utilize ePHR." (p. i)

As described above, ePHRs have remained relatively under-researched and the drivers/motivations for ePHR adoption have yet to be sufficiently explored (Randeree, 2009). It has been noted that the study of ePHR adoption is difficult, as the traditional predictors of adoption and usage do not always apply (Randeree, 2009). Traditional models such as the Technology Acceptance Model (TAM) may not directly relate (Lafky & Horan, 2008), as ePHRs are a new and novel technology for users, and the constructs of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) may be more difficult to measure (Lafky & Horan, 2008). This is due to the fact that PEOU is difficult for a prospective ePHR user to assess when they have not previously used the technology (as mentioned previously, only 7% of people in the United States have used an ePHR) (Lafky & Horan, 2008). PU of an ePHR has previously been difficult to measure, as prospective users did not have a well-defined task for which to use the ePHR technology (Lafky & Horan, 2008). Thus ePHR adoption studies should examine and incorporate theory and models from other disciplines and/or different IS theories in order to more successfully understand the adoption of this information technology. It has been noted that "Widespread adoption and use of PHRs will not occur unless they provide perceptible value to users, are easy to learn and easy to use, and have associated costs (both financial and effort) that are easily justified related to the PHR's perceived value." (Tang, et al., 2006, p. 123). These factors in a health related context can be best understood through the PMT response efficacy construct (which encompasses perceptible value), self-efficacy

construct (which encompasses ability to learn and use) and response cost construct (which encompasses associated cost/benefit). Therefore this research utilizes PMT (from the health behaviour discipline) in combination with TTF (from IS theory) which provides the missing task element noted above, and PAM (from self-management readiness literature) in an effort to better understand the adoption of ePHRs.

It can be concluded that while prior PHR/ePHR adoption studies exist, they have produced mixed results, and are not typically theoretical, empirical studies. Only one known study (Morton, 2011) examined ePHR adoption by chronic disease patients. Given that one of the groups cited as having strong potential to benefit from the use of PHR/ePHRs are people with chronic diseases, this current theoretically based, empirical research study attempts to understand the health related and technology factors involved in ePHR adoption for chronic disease patients, which makes this research unique and distinct from prior research. In addition, the focus on the use of an ePHR for the task of self-management of a chronic disease led to the use of specific theories and concepts (i.e., PMT, TTF, PAM) which were a natural fit for this research. Chapter 3 now explores these relevant theories and concepts which form the basis of the research model.

Chapter 3. Theoretical Background

This study combines Protection Motivation Theory/Ordered Protection Motivation Theory (PMT/OPMT), Task-Technology Fit (TTF) and Patient Activation Measure (PAM) in the context of understanding ePHR adoption by chronic disease patients. The dependent variable in this study is ePHR Adoption Intention, and the proposed study examines how PMT, TTF and PAM may affect this. In addition, as a secondary objective, this study examines the effects that Educational Interventions (EI) have on certain elements of the model. This chapter provides a thorough literature review of each of these theoretical topics.

3.1. Protection Motivation Theory (PMT)

Protection Motivation Theory (PMT) is a widely adopted framework for the prediction of health-related behaviour (Milne, et al., 2000). PMT was originally developed by Rogers (1975), and subsequently redesigned (Maddux & Rogers, 1983) to address early limitations of the theory. PMT is a comprehensive model, based on the Health Belief Model. Both PMT and the Health Belief Model are premised on expectancy-value theory, as well as the inclusion of a cost-benefit analysis (Prentice-Dunn & Rogers, 1986). However, the PMT theory has proven to be superior to the Health Belief Model with respect to the prediction of preventative behaviours (Seydel, et al., 1990), such as disease self-management. PMT can be applied to any threat situation, and not simply health related circumstances (Prentice-Dunn & Rogers, 1986). Research that utilizes PMT is typically from one of two main streams: i) framework to develop and evaluate persuasive communications, and; ii) prediction of health related behaviours (Norman, et al., 2005). While this research addresses each of these areas, it is this second stream which is the main focus of this study.

The PMT model itself contains two specific appraisals (based on information held by the individual) in a cognitive mediating process, namely threat appraisal (focusing on the source of the threat and likelihood and potential severity of the threat actually happening) and coping appraisal (focusing on coping responses that individuals use to deal with the threat). These two appraisals lead to protection

motivation (focusing on the individual's intention to perform recommended behaviours) (Norman, et al., 2005). Modes of coping can be maladaptive (e.g., avoidance, denial, etc.) or adaptive (e.g., changes in health behaviour such as weight loss, etc.). This is presented graphically below in Figure 1.

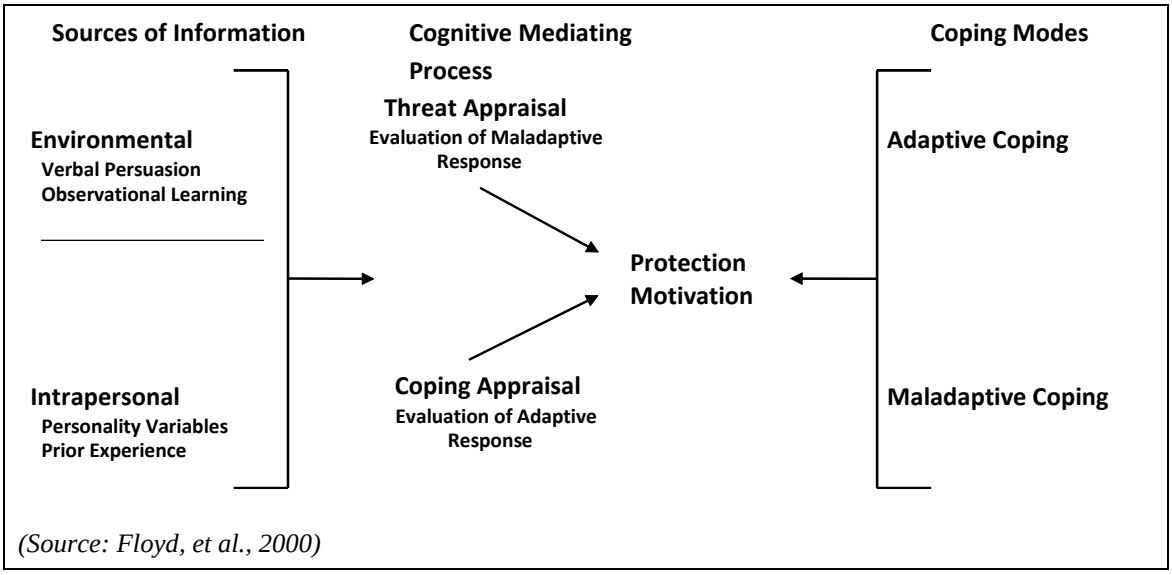
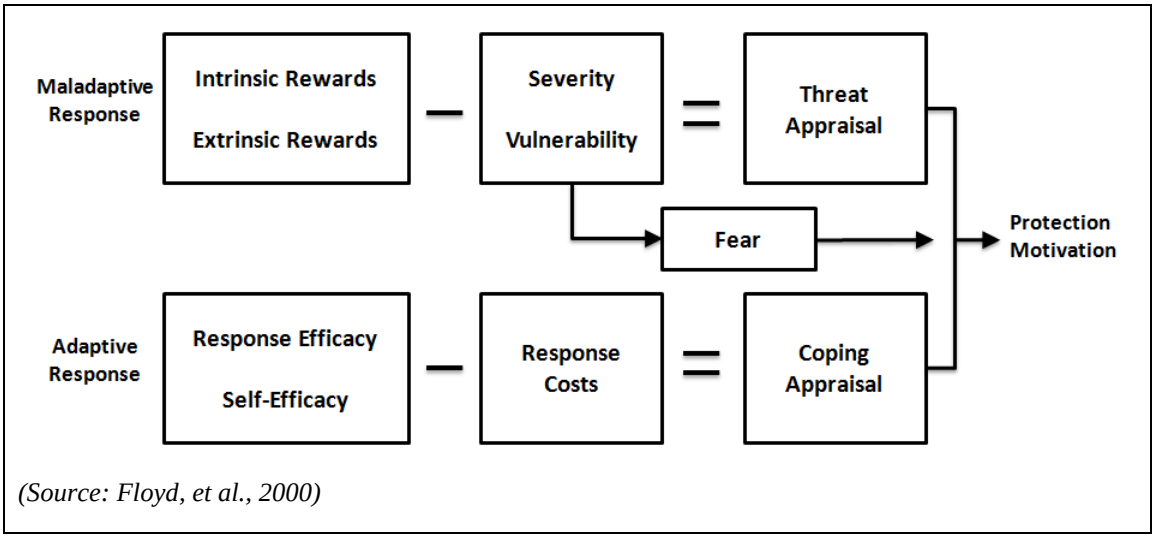


Figure 1 – Protection Motivation Theory

To better understand the PMT cognitive mediating process and coping modes, one must examine the individual items that they are comprised of, shown in Figure 2. Threat Appraisal is considered as a function of rewards (intrinsic and extrinsic) less the threat perception (severity and vulnerability) (Floyd, et al., 2000). Intrinsic rewards are typically pleasure related (e.g., pleasure gained from continuing to smoke) and extrinsic (e.g., social approval from friends who drink and wish you to continue consuming alcohol). Threat perception includes severity, defined as "how serious the individual believes that the threat would be to his or her own life" (Milne, et al., 2000, pg. 108) and could include thinking such as "my coronary heart disease could reduce my life expectancy". Vulnerability is defined as "how personally susceptible an individual feels to the communicated threat" (Milne, et al., 2000, pg. 108) and could include thinking such as "given my family history and lifestyle, I am more likely to be diagnosed with cancer". These items of threat perception lead to fear, defined as "how much fear the threat evokes for the individual" (Milne, et al., 2000, pg. 109) and could include thinking such as "the thought of being

diagnosed with cancer makes me scared". Maladaptive responses occur when the rewards are considered by the individual to be higher than the severity, vulnerability and fear.



(Source: Floyd, et al., 2000)

Figure 2 – Cognitive Mediating Process and Coping Modes

The lower part of the process contains the adaptive response coping appraisal items. Here, response efficacy, defined as "beliefs about whether the recommended coping response will be effective in reducing [the] threat to the individual" (Milne, et al., 2000, pg. 109) includes thinking such as "if I change my diet and exercise more, I can lose weight and live longer". Self-efficacy is defined as "an individual's beliefs about whether he or she is able to perform the recommended coping response" (Milne, et al., 2000, pg. 109), and involves thinking such as "changing my diet and exercise habits would be easy for me to do". Finally, response costs, defined as "beliefs about how costly performing the recommended response will be to the individual" (Milne, et al., 2000, pg. 109) include both tangible (e.g., monetary, etc.) and intangible (e.g., time, etc.) costs. Adaptive responses occur when the efficacy items are larger than the costs. In this model, protection motivation can be thought of as intention to perform a behaviour (Milne, et al., 2000) such as ePHR adoption, which can be considered an adaptive coping response (in that using an ePHR will involve a positive change in health related factors). As stated by Prentice-Dunn and Rogers (1986), "Protection motivation is best indexed by behavioral intentions, which are related to overt behavior according to Fishbein's well-known theory of reasoned action." (p. 158).

PMT has been shown to be a strong predictor of both intentions and behaviour (Blanchard, et al., 2009). The Blanchard study (2009) indicated that threat appraisal variables (i.e., Severity and Vulnerability) appear to have less effect on intention than coping appraisal variables (i.e., Self-Efficacy, Response Efficacy and Response Costs) (Blanchard, et al., 2009). Two meta-analyses (Floyd, et al., 2000; Milne, et al., 2000) completed on PMT confirm this finding, but still conclude that all PMT constructs have significant relationships with intention and behaviour. As shown below in Table 3, the effect sizes for Response Efficacy, Self-Efficacy and Response Costs are larger than those for Severity and Vulnerability. In addition, another meta-analysis (Webb & Sheeran, 2006) showed that in PMT studies involving interventions (e.g., educational interventions, etc.) the interventions had large effect sizes on behavioural intentions. Overall, PMT's predictive ability for both intention and behaviour in health situations with interventions make it particularly suited to studying ePHR adoption intention in the context of this study, which also incorporates educational interventions.

Table 3 – PMT Meta-Analysis Summary

	Floyd et al. (2000)[a]	Milne et al. (2000)[b]		
	Intention and Behaviour	Intention	Concurrent Behaviour	Future Behaviour
Severity	0.39***	0.10***	0.10***	0.07
Vulnerability	0.41***	0.16***	0.13***	0.12**
Response Efficacy	0.54***	0.29***	0.17***	0.09
Self-Efficacy	0.88***	0.33***	0.36***	0.22***
Response Costs	-0.52***	-0.34***	-0.32***	-0.25***
Protection Motivation	N/A	N/A	0.82***	0.40***

*Note: [a] Reported coefficients are d_+ = sample weighted standardized mean differences; [b] Reported coefficients are r_+ = sample weighted average correlations; ** $p<0.01$; *** $p<0.001$. (Source: Norman, et al., 2005)*

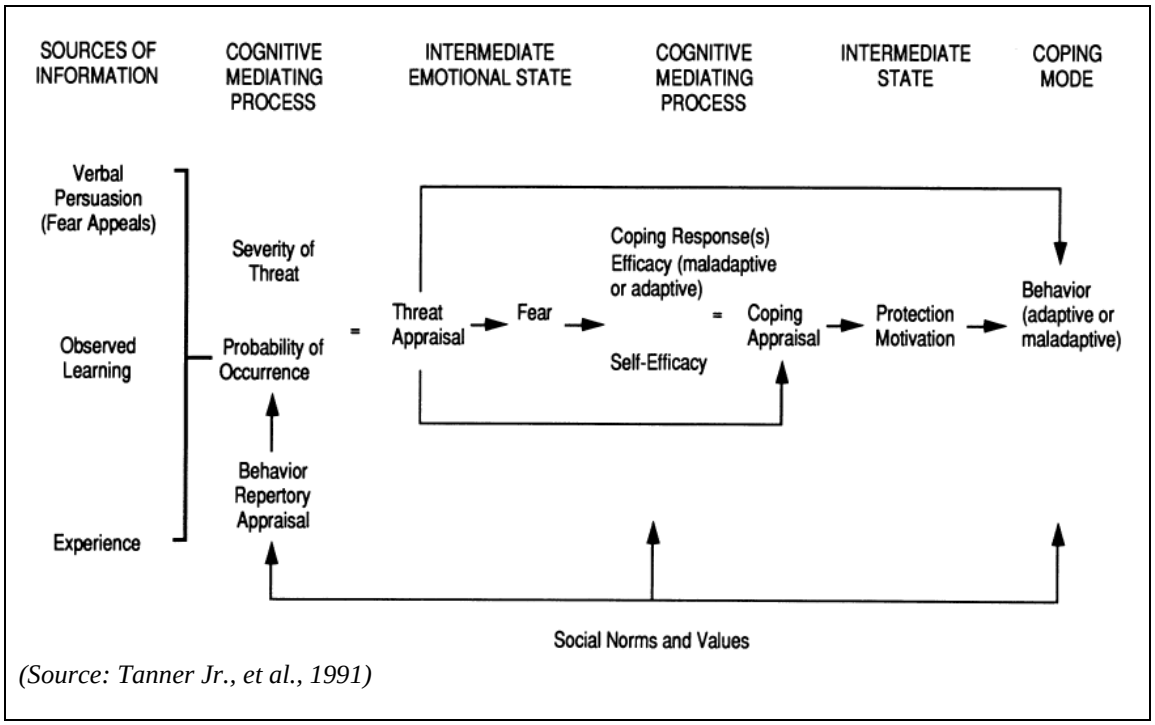
PMT has previously been applied to a number of medical situations and conditions including smoking cessation (Plotnikoff & Trinh, 2010), alcohol consumption (Plotnikoff & Trinh, 2010), non-compliance behaviours in renal transplant patients (Rudman, et al., 1999), exercise (Plotnikoff & Higginbotham, 2002), breast cancer (Rippetoe & Rogers, 1987), cardiac rehabilitation and exercise (Blanchard, et al., 2009), coronary artery disease and exercise (Tulloch, et al., 2009), and even fabricated medical conditions (i.e., Crevelling's disease) (Brouwers & Sorrentino, 1993). While PMT has typically been utilized to investigate the factors involved in people making health related changes, it has been

previously proposed in the context of health related technology adoption. Specifically, Chen and Lee (2008) proposed an examination of the factors affecting the acceptance of a computerized physician order entry system, indicating the applicability of PMT for health information technologies. PMT, while typically applied in health related situations, has also been successfully used (either directly or as a conceptual foundation) in IS contexts, such as the use of anti-spyware and anti-malware software protective technologies (Chenoweth, et al., 2009; Lee & Larsen, 2009), home computer security behaviour (Anderson & Agarwal, 2010), online social media (Banks, et al., 2010), security policy compliance in organizations (Herath & Rao, 2009b; Johnston & Warkentin, 2010), anti-plagiarism software adoption (Lee, 2010), and other information security measures (Workman, et al., 2008). The focus of this study on the intention to adopt a health related IS makes the use of PMT as the foundation theory particularly suitable.

3.2. Ordered Protection Motivation Theory (OPMT)

While this research mainly draws on PMT, a variation of this model, namely Ordered Protection Motivation Theory (OPMT) was used in the formulation of the research model. A study by Tanner et al. (1991) posited that the PMT threat and coping appraisal processes occur sequentially (rather than concurrently), as shown in Figure 3. In the OPMT model, there is a mediation process whereby threat appraisal affects behaviour indirectly, with both fear and coping appraisal acting as the mediators (Ho, 2000). The study by Tanner et al. (1991) found support for the protection motivation appraisal process to be an ordered one, with threat appraisal happening before coping appraisal, and concluded "support is provided for the OPM [Ordered Protection Motivation] model in which threat appraisal occurs prior to coping appraisal" (Tanner Jr., et al., 1991, p. 43). The sequential nature of OPMT is based on earlier work by Lazarus (1968) which notes "once threat appraisal takes place, information about possible lines of coping (secondary appraisal) is given urgency, or search processes relevant to coping are activated" (p. 197). Lazarus further concluded that "it is expected that as the threat (i.e., value of the stimulus) information becomes salient, emotion-focused attention will increase the significance according to finding

a coping behaviour" (Tanner Jr., et al., 1991, p. 38). This early work by Lazarus later shaped the cognitive-relational theory of emotion and coping, which examined cognitive appraisal (typically of a stress related situation) along with coping processes (Lazarus & Folkman, 1987). For the purposes of this research, OPMT was considered to be more applicable than the work by Lazarus, as OPMT typically focuses on threat and coping appraisal processes in health related contexts such as this one. Other prior literature (see Scherer, 1984; 1988) also posited an ordered appraisal process, in that "individuals appraise their environment for relevant/salient information and then appraise their ability to cope with the assessed situation." (Tanner Jr., et al., 1991, p. 43). Finally, traditional PMT studies have also concluded that the order of the information presented has an effect on the extent to which people exhibit an adaptive rather than a maladaptive response (Prentice-Dunn, et al., 2001). That study concluded that "[The] results demonstrate the threatening health information energizes one to act in both adaptive and maladaptive ways, and that coping information decreases the tendency to respond maladaptively to the health threat. [The results] also suggest that the order of presentation of the information may affect the extent to which people respond adaptively." (Prentice-Dunn, et al., 2001, p. 81). It is therefore logical to conclude that if the ordering of the information presented matters, the ordering of the constructs which are manifestations of that information should also matter, adding credence to the OPMT variation of the PMT model. To the best of my knowledge, this is only the second known study to apply OPMT in an IS context. While earlier studies have employed PMT in an IS context (as described above in Section 3.1), only one known study (Johnston & Warkentin, 2010) has applied a variation of PMT, namely the Fear Appeals Model (FAM), which is in essence indistinguishable from OPMT.



(Source: Tanner Jr., et al., 1991)

Figure 3 – Ordered Protection Motivation Theory

A more parsimonious representation of OPMT model that was adopted for this study is shown in Figure 4. In this model, the key constructs of Severity and Vulnerability form the first stage (threat appraisal), while the key constructs of Response Efficacy and Self-Efficacy form the second stage (coping appraisal). The threat appraisal leads to a level of fear in the individual. One important element of OPMT is the role that fear plays in the model. In the original PMT model, fear is not considered to be an essential element in the cognitive appraisal process (Ho, 2000). Fear is an element of OPMT, as shown in Figures 3 and 4. However in the OPMT research model examined by Ho (2000), "fear was not found to be a crucial mediator to coping appraisal as hypothesized from an OPM [Ordered Protection Motivation] paradigm" (p. 116). More importantly, in the Ho (2000) study, fear was found to primarily affect intention to adopt maladaptive coping responses (e.g., denial, etc.) rather than intention to adopt adaptive coping responses (e.g., exercising, quitting smoking, etc.) More specifically, the fear component focused the individual's attention on their range of maladaptive coping responses (Ho, 2000), thus indicating that including a fear construct is not an essential component for studies that are specifically examining

adaptive coping appraisal responses and their relationship with behavioural intentions. The second stage in the model is the coping appraisal stage, represented by the Response Efficacy and Self-Efficacy constructs. This staged assessment of the threat followed by coping appraisal then leads to Protection Motivation, which is represented by Intentions (e.g., behavioural intentions).

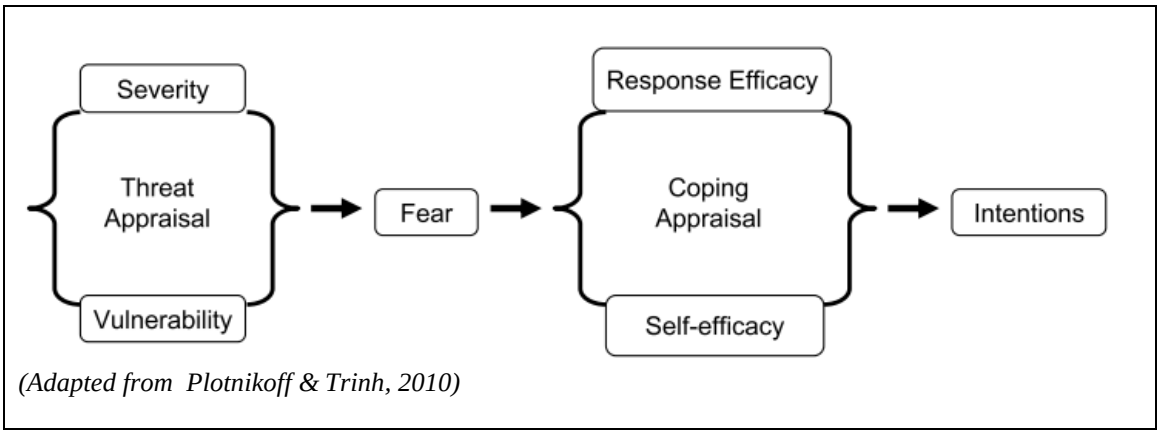


Figure 4 – Parsimonious OPMT Conceptual Model

3.3. Task-Technology Fit (TTF)

TTF theory was originally proposed by Goodhue (1995) who indicated the need for "some specific user evaluation construct, defined within a theoretical perspective that can usefully link underlying systems to their relevant impacts." (Goodhue, 1995, p. 1827) He proposed TTF to fill this need (Goodhue, 1995). TTF includes multiple dimensions related to task requirements, technology functionalities and individual abilities, which led to task-technology fit and performance, as shown in Figure 5. User evaluations of the IT are used to assess TTF, as according to Goodhue "when users evaluate systems, they will be sensitive to the same effects which lead from task, technology, and individual performance. That is, users will give evaluations based on the extent to which systems meet their needs and abilities" (Goodhue, 1995, p. 1830). TTF theory proposes that a better fit between technology and task will lead to enhanced performance, either in terms of faster performance, or in terms of more effective accomplishment of tasks (Goodhue, 1995). It is this second element of performance that this research study examines, in that better fit between the ePHR technology and self-management task will lead to more effective Type 2 Diabetes self-management. In addition to task and technology,

there is also an individual element, whereby TTF includes "the extent that technology functionality matches task requirements and individual abilities" (Goodhue, 1995, p. 1829), in that the technology must fit both the task and the individual. In summary, TTF includes the direct influences that task requirements, technology characteristics and individual abilities have on user evaluations of IT, as well as "the extent to which technology functionality matches task requirements and individual abilities" (Ammenwerth, et al., 2006, p. 3).

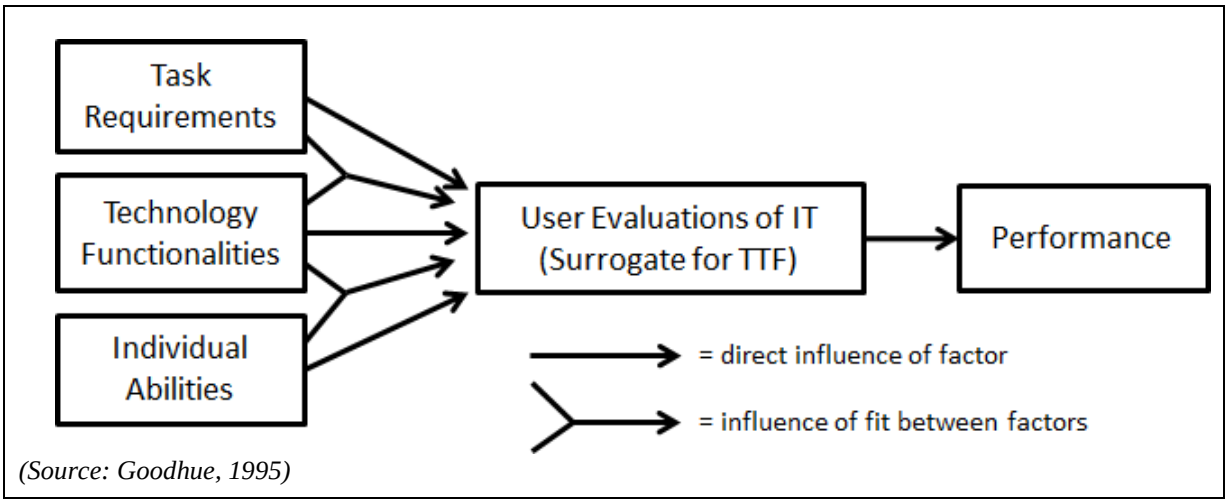


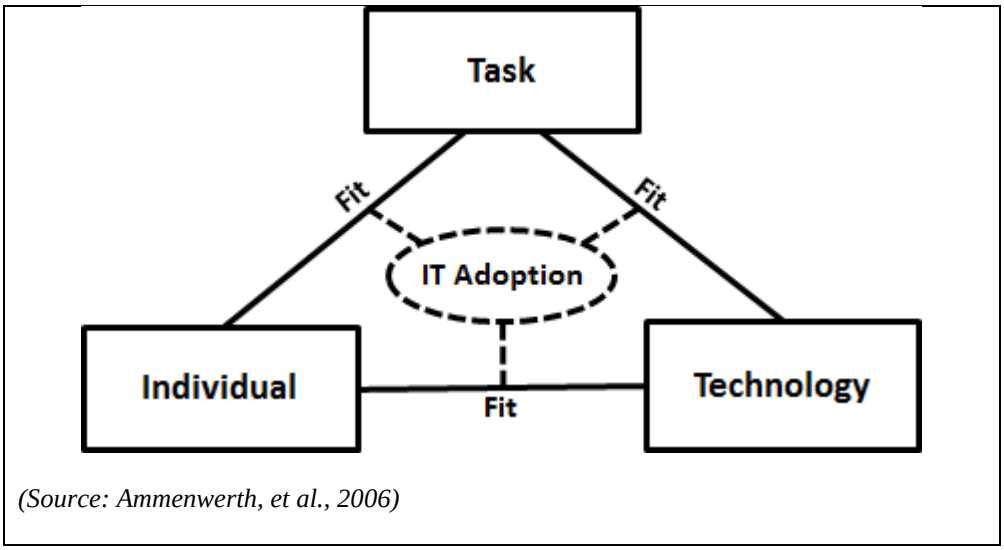
Figure 5 – Task Technology Fit

TTF has been used in a wide variety of contexts, including eCommerce (Klopping & McKinney, 2004), hotel information systems (Lam, et al., 2007) software maintenance (Dishaw & Strong, 1999), mobile locatable information systems (Junglas, et al., 2008), mobile commerce (Lee, et al., 2007), knowledge management systems (Lin & Huang, 2008), web-based spatial decision support systems (Jarupathirun & Zahedi, 2007), learning management systems (McGill & Klobas, 2009) and similar to this study, electronic medical records (Kilmon, et al., 2008).

One noted limitation of TTF is that it does not overtly consider the fit between the individual and the task (Ammenwerth, et al., 2006), as shown in Figure 5 (note that the fit between task–technology and technology–individual are included but not the fit between task–individual). Ammenwerth et al. (2006) therefore proposed an alternate TTF framework known as the FITT (Fit between Individuals, Task and Technology), shown in Figure 6, which involves the fit between the user abilities (e.g., self-efficacy,

motivation, etc.), technology (e.g., functionality, usefulness, performance, etc.) and task (e.g., complexity, effort, etc.). Subsequent case study based research found support for the FITT framework (Tsiknakis & Kouroubali, 2009). A similar triangular conceptual modelling of FITT was also proposed and evaluated by Liu et al. (2011) in a Decision Support Systems (DSS) context. The inclusion of the fit between the task and the individual is something which is very important in voluntary situations (such as ePHR adoption and use). For voluntary tasks, users must be motivated to perform the task and see a 'fit' between themselves and performance of the task. Therefore this study incorporates PMT which addresses the motivational component (i.e., threat and coping appraisals) and the Patient Activation Measure (PAM), discussed below, that addresses the individual–task fit element. Additionally, Ammenwerth et al. (2006) suggested deliberate interventions as a way to manipulate and affect the FITT dimensions, which have been incorporated in this research study through educational interventions. Again, it is important to note that for the purposes of this study, the technology is an ePHR, the individual is a Type 2 Diabetes patient and the task is Type 2 Diabetes self-management using an ePHR. Due to the fact that self-management of a chronic disease involves a time consuming set of complex tasks, the use of TTF and its focus on the fit between task, technology and the individual made it more appropriate for this study than the use of other IS theories such as TAM.

Recently, studies have simply included a single TTF construct (Klopping & McKinney, 2004; Klopping & McKinney, 2006; Lam, et al., 2007; McGill & Klobas, 2009) rather than distinct task requirements, technology functionalities and individual abilities constructs. In situations where study participants may not all use the identical IS (e.g., people from different organizations using a company-specific knowledge management systems) (Lin & Huang, 2008), where participants were in a laboratory experiment (i.e., rather than an actual real-life use setting) (Jarupathirun & Zahedi, 2007) or where participants did not actually use an IS but rather are required to think of the task and technology on a conceptual level, a Perceived Task-Technology Fit (PTTF) construct has been used. It is this perceived task-technology fit that is used in this study, as participants evaluated their perceptions of ePHR usage rather than actual usage.



(Source: Ammenwerth, et al., 2006)

Figure 6 – FITT (Fit between Individuals, Task and Technology) Framework

3.4. Patient Activation Measure (PAM)

The Patient Activation Measure (PAM) is a "process for conceptualizing and operationalizing what it means to be 'activated' " (Hibbard, et al., 2004, p. 1005). Specifically, the concept of 'activated' is defined as the belief that "patients have important roles to play in self-managing care, collaborating with providers, and maintaining their health. [Activated people] know how to manage their condition and maintain functioning and prevent health declines; and they have the skills and behavioral repertoire to manage their condition, collaborate with their health providers, maintain their health functioning, and access appropriate and high-quality care." (Hibbard, et al., 2004, p. 1010). In essence, PAM assesses a person's beliefs, motivation, knowledge, skills, confidence and actions for health care self-management (Greene & Hibbard, 2012; Mosen, et al., 2007; Remmers, et al., 2009). PAM was initially proposed by Hibbard et al. (2004) as the conceptualization of patient activation was deemed to be empirically underdeveloped (Hibbard, et al., 2004). Originally assessed through a 21-item scale with a focus towards chronic care patients (Hibbard, et al., 2004), a shorter validated scale was proposed and evaluated by the same researchers one year later (Hibbard, et al., 2005), again with a focus towards chronic disease patients. This reduced and validated 13-item scale (see Appendix B) is used to create a single calculated raw score and ultimately an adjusted final score that ranges between 0 and 100. The use of the scale and

scoring calculation tools is licensed by Insignia Health, with no-charge access provided to academic researchers. While theoretically the PAM score can fall between 0 and 100 points, most patient's adjusted scores fall within the 35 to 95 point range (Greene & Hibbard, 2012) as shown in Figure 7. Those at the low end of the scale tend to be passively involved in their care and do not believe in the need for the patient to take an active role in the self-management of their health, while those scoring at the high end of the scale tend to take a proactive role in their health and engage in more self-management behaviours. (Greene & Hibbard, 2012)

The results of the PAM scoring system places individuals into one of four stages of activation, as described below and shown in Figure 7. In the figure, the different stages along the X-axis represent four activation stages, and the values above the bars indicate the approximate adjusted PAM score required to move to the next stage, as described below.

Stage1. Patient believes that an active role in health self-management is important (adjusted score between 35.0 and 63.2)

Stage2. Patient has the confidence and knowledge to take action in the self-management of their health (adjusted score between 63.2 and 77.5)

Stage3. Patient is taking action in the self-management of their health (adjusted score between 77.5 and 91.6)

Stage4. Patient can self-manage their health even under stressful conditions (adjusted score > 91.6)

For example, a score of 75 would mean that the individual is late Stage 2, and has the confidence and knowledge to take action in the self-management of their health and chronic condition. They are also almost ready to start taking action, which will be their next potential stage. A score of 80 would mean that the individual has just started to take action in the self-management of their health and chronic condition, and places them in early Stage 3. A score less than 35 indicates they are not yet ready for self-management of their health condition.

(Adapted from Hibbard, et al., 2005)

Figure 7 – Patient Activation Measure (PAM) Stages

PAM has been successfully used in multiple research studies since its development in 2004, including those examining general chronic illnesses (Dixon, et al., 2009; Mosen, et al., 2007) specific chronic conditions such as Diabetes, (Lorig, et al., 2010; Lorig, et al., 2009; Rask, et al., 2009; Remmers, et al., 2009) and overall general health (Fowles, et al., 2009; Greene & Hibbard, 2012). The focus PAM places on chronic conditions and the previous use of PAM in research involving people with Diabetes confirms the applicability of PAM to this research study.

3.5. Educational Interventions (EI)

Intervention theory has been part of academic research for decades, with early intervention theory research such as "Intervention Theory and Method: A Behavioral Science View" (Argyris, 1970). Later work in educational interventions was completed by Fishbein and Middlestadt (1987) based on the Theory of Reasoned Action. Specifically, the work shows how the Theory of Reasoned Action can "serve as a framework for developing educational interventions directed at changing these behaviors. In illustrating the applicability of the theory in this behavioral domain, the necessity of tailoring one's intervention strategy to a given behavior in a given population is emphasized." (Fishbein & Middlestadt, 1987, p. 361). Fishbein and his co-authors used the Theory of Reasoned Action in the development of educational interventions in a number of areas including drug use (Fishbein & Middlestadt, 1987) and AIDS related behaviours (Fishbein, 1990). One of the most important educational intervention findings detailed by Fishbein (1995) that is crucial in this current research study is that "there is abundant evidence that information in and of itself can produce behavior change" and that providing "types of information (e.g., about the consequences of performing the behavior, groups who support behavioral performance, or ways to overcome barriers to behavioral performance) can be effective" (Fishbein, 1995, p. 247).

Educational interventions for chronic diseases such as asthma, arthritis, Diabetes and hypertension have shown promising results (Warsi, et al., 2004). Specifically, education programs, which "emphasize the role of patient education in preventive and therapeutic health care activities" (Warsi, et al., 2004, pg. 1641) can be of assistance to chronically ill patients. Self-management education has been shown to have a moderate effect overall, but stronger for selected chronic diseases (Warsi, et al., 2004), specifically those where the self-management education objectives are easy to define and the treatment or intervention response is more conducive to self-management programs and education. For example, Warsi et al. (2004) indicate that the goals for arthritis education and treatments for the disease may be "less affected by self-management education programs" (Warsi, et al., 2004, pg. 1647) than for example Diabetes, which has specific blood glucose level goals or hypertension which has specific blood pressure goals, and well defined educational interventions to assist patients in meeting these goals. This is a possible reason

why Warsi et al. (2004) found that self-management education programs had statistically significant effects (small to medium) for some, but not all chronic diseases (Warsi, et al., 2004). Chronic and other disease educational intervention programs have shown promise for Diabetes, asthma, and HIV/AIDS among others. Table 4 summarizes the salient literature involving educational interventions for chronic and other conditions. Most studies show significant positive outcomes related to educational interventions. Of notable importance, meta-analyses (Norris, et al., 2001; Norris, et al., 2002) investigating the effects of educational interventions amongst people with Type 2 Diabetes show improvements in a number of areas including glycemic (blood sugar control, typically measured via H_bA1_C), disease knowledge, self-monitoring, etc.

Table 4 – Educational Intervention Studies Summary

Citation	Chronic/Disease Condition	Reported Education Intervention Information*
(Brown, 1999)	Diabetes (meta-analysis)	• Literature supports effectiveness of educational interventions for improving physical and psychosocial health • More research needed on how to best achieve these improved outcomes required
(Butz, et al., 2005)	Asthma	• Demonstrated increase in asthma knowledge, self-efficacy, quality of life and reduction in hospital visits • Increase in asthma knowledge leads to self-efficacy which should lead to improved quality of life • Interactive parent-child intervention significantly increased both the parents and the child's asthma knowledge, child self-efficacy but not quality of life for rural children with asthma
(Fruin, et al., 1992)	Cardiovascular Disease	• Coping strategies to deal with perceived threats may be influenced by the perceived efficacy of the behaviour and the person's ability to perform the behaviour
(Guevara, et al., 2003)	Asthma (meta-analysis)	• Asthma education demonstrated improved lung function, self-efficacy and reductions in morbidity, school absenteeism, days of restricted activity, night sleeping disturbances and hospital visits • Positive changes in morbidity outcomes more prevalent in severe asthma patients
(Gong, et al., 2009)	HIV/AIDS	• Significant positive effects on HIV/AIDS knowledge, self-efficacy, response efficacy, response cost, vulnerability and protective (i.e., condom) measures • Intervention effect sustained over 2 year period • Interventions more effective on coping perceptions versus threat perceptions

(McCusker, et al., 1992)	AIDS	• Basic educational interventions improved AIDS knowledge • Enhanced intervention (focus on personal susceptibility, situational analysis and skill building) led to greater self-efficacy
(Mesters, et al., 1994)	Asthma	• Participating parents had more knowledge, higher self-efficacy scores, decreased health care practitioner and hospital visits, reduction in asthma severity, and performed more self-management behaviours • Follow-up study indicated that resultant changes were sustained
(Norris, et al., 2001)	Type 2 Diabetes (meta-analysis)	• Meta-analysis of 72 studies of the effectiveness of self-management training for people with Type 2 Diabetes • Results indicate improved knowledge, frequency and accuracy of self-monitoring of blood glucose, dietary habits, and glycemic control in studies with short follow-up (<6 months)
(Norris, et al., 2002)	Type 2 Diabetes (meta-analysis)	• Meta-analysis of 31 studies of self-management education for people with Type 2 Diabetes and the effects on glycemic control • Improvements shown with H_bA1_C decreases of 0.76% (immediate) and 0.26% (at 1-3 months and >4 months) • Improvements in H_bA1_C also related to increased time spent with Type 2 Diabetes educator • More interventions needed to maintain longer term glycemic control
(Prentice-Dunn, et al., 2001)	Breast Cancer	• High coping response messages led to more positive behavioural intentions, more rational problem solving and less fatalism
(Rippetoe & Rogers, 1987)	Breast Cancer	• High-response efficacy and high-self-efficacy interventions strengthened adaptive coping and did not foster any maladaptive coping
(Sigurdardottir, et al., 2007)	Type 2 Diabetes	• Education interventions positively affect knowledge, self-care skills and physiological aspects • Self-care skill teaching interventions more effective • Self-care instruction improves self-efficacy
(Stanley & Maddux, 1986)	General Health	• Exercise related educational intervention designed to increase perceptions of response efficacy and self-efficacy produced stronger behavioural intentions
(Wurtele & Maddux, 1987)	Cardiovascular Disease	• Exercise related educational intervention designed to increase perceptions of self-efficacy produced stronger behavioural intentions

** Reported information may include both results from the specific study as well as other literature reviewed in that study.*

While the interventions discussed thus far typically involve chronic disease education, there is prior literature support for educational interventions (e.g., product demonstrations, training) with respect to technology. Specifically, Venkatesh and Davis (2000) indicate that TAM theorizes that external variables such as training affect intention, mediated by perceived usefulness and perceived ease of use (Venkatesh

& Davis, 2000). TAM3 is even more specific, listing training as a 'Post-implementation Intervention' which can potentially influence Perceived Ease of Use and Perceived Usefulness (which in turn influence Behavioural Intention) (Venkatesh & Bala, 2008). This current study examines the effects of educational interventions on technology adoption, with one of the two interventions involving basic information versus advanced product demonstration on the use and benefits of an ePHR for Type 2 Diabetes self-management. This advanced product demonstration incorporates many of the elements of training and therefore the prior literature regarding training (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) is applicable.

While the preceding educational intervention discussion focused on self-management education, educational interventions designed to elicit a sense of concern or fear are very common in studies employing PMT. As described in Milne et al. (2000) there are three types of PMT studies, namely correlational design, health-education intervention and experimental manipulations of specific PMT variables. Two of these designs (i.e., health-education intervention and experimental manipulations of specific PMT variables) both involve educational interventions that manipulate the PMT variables. Many previous PMT studies have successfully employed educational interventions that manipulate severity and vulnerability, including studies involving cancer (Courneya & Hellsten, 2001; Graham, et al., 2006; McMath & Prentice-Dunn, 2005; Prentice-Dunn, et al., 2001; Rippetoe & Rogers, 1987; Seydel, et al., 1990), coronary heart disease/cardiovascular disease (Milne, et al., 2002; Wurtele & Maddux, 1987), fictitious disease (Brouwers & Sorrentino, 1993) and information security (Johnston & Warkentin, 2010). A meta-analysis of intervention studies (Webb & Sheeran, 2006) showed that studies involving the provision of risk awareness material (i.e., a form of threat based educational intervention) had a large effect size (i.e., $d+ = 0.56$) on behavioural intentions.

Chapter 4. Research Model and Hypotheses

Based on the combination of the contextual and theoretical background provided, a research model designed to examine the relationships between the different variables hypothesized to affect ePHR adoption was developed. Efforts have been made to ensure that only the most salient items have been included in the parsimonious research model that assesses and predicts ePHR adoption intention by chronic disease patients for self-management. This research model, which combines OPMT with TTF and incorporates PAM is shown in Figure 8, followed by descriptions of the constructs, proposed hypotheses and prior literature and/or logical support for the relationships.

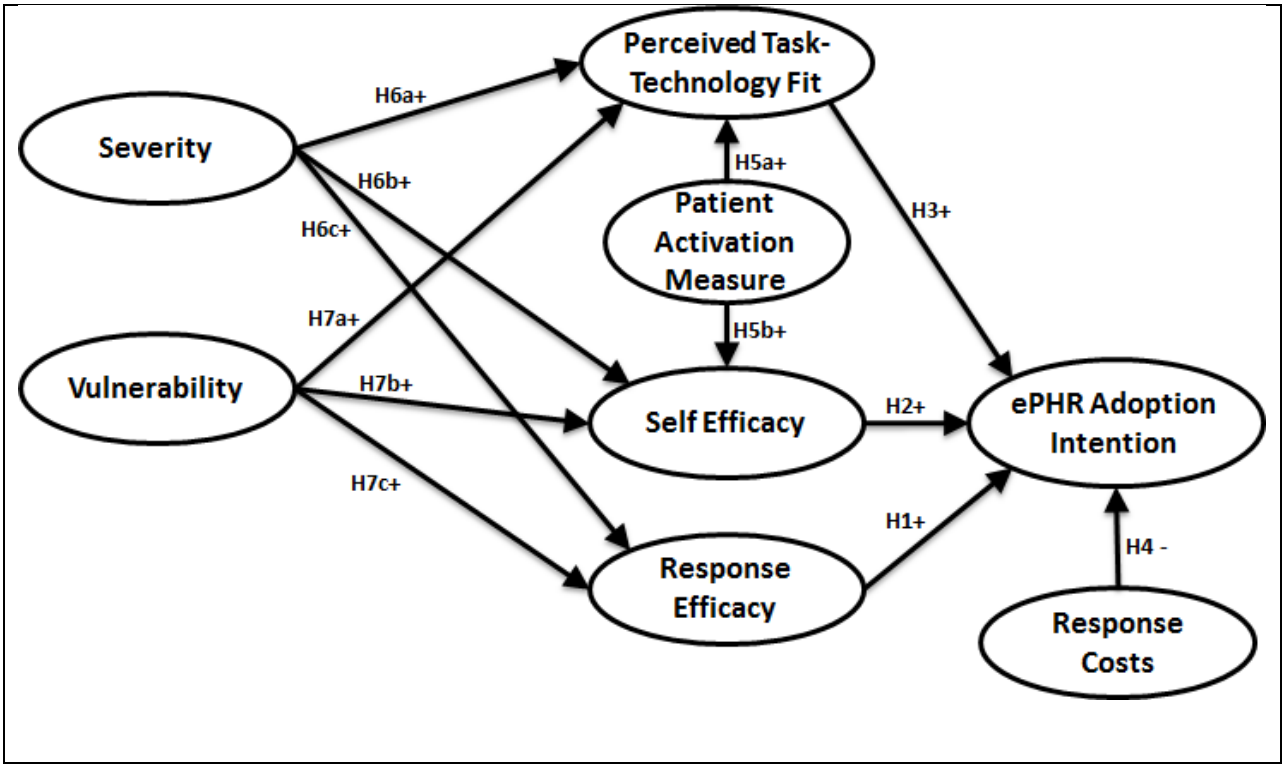


Figure 8 – Research Model

4.1. ePHR Adoption Intention (ADOPT):

The endogenous construct in this research study is ePHR Adoption Intention, as behavioural intentions are typically the key dependent variable in PMT studies, as evidenced by meta-analyses (Floyd, et al., 2000; Milne, et al., 2000) as well as seminal research completed by the developer of PMT (Rogers & Prentice-Dunn, 1997). In addition, while the dependent variable in TTF is typically Performance

Impact, many TTF studies include intention to adopt/use either with a direct relationship with TTF (Dishaw & Strong, 1998; Klopping & McKinney, 2004; Klopping & McKinney, 2006; Lam, et al., 2007; Liu & Goodhue, 2012; Shih & Chen, 2013; Yen, et al., 2010) and/or via a mediated relationship with TTF through one or more of Perceived Usefulness, Perceived Ease of Use, Perceived IT Beliefs, Performance Expectancy, Perceived Playfulness and/or Attitude (Chang, 2008; Kim, et al., 2010; Klopping & McKinney, 2004; Klopping & McKinney, 2006; Kuo & Lee, 2011; Lam, et al., 2007; Lee, et al., 2009; Shih & Chen, 2013; Yen, et al., 2010; Zhang, et al., 2010). Previous studies have shown specifically in a health-related behavior environment that intention to perform a behavior was highly correlated with actual behaviour (Graham, et al., 2006; Or, et al., 2008), and therefore, while this study examined ePHR adoption intention, this intention should correlate with actual use. In addition, intention is highly correlated with actual use in prior IS literature. Most notably, TAM posits that intention is a good predictor of usage, with the TAM literature stating "Research in psychology and TAM itself suggest that users' intention to use is the single best predictor of actual system usage" (Davis & Venkatesh, 1996, p. 20). A later meta-analysis of the TAM literature confirmed this, indicating a significant positive relationship between intentions and usage, with a weighted mean effect size of 0.46 (Yousafzai, et al., 2007).

4.2. Response Efficacy (RE):

This adaptive coping appraisal construct is defined as "beliefs about whether the recommended coping response will be effective in reducing threat to the individual" (Milne, et al., 2000, p. 109). In this research it is operationalized as the individual's beliefs that the use of an ePHR will lead to better Type 2 Diabetes self-management (which in turn should reduce the threat to his/her health). Studies show RE to have a significant relationship with behavioural intentions in health related contexts (Blanchard, et al., 2009; Chenoweth, et al., 2009; Courneya & Hellsten, 2001; Graham, et al., 2006; Norman, et al., 2003; Plotnikoff & Higginbotham, 2002; Plotnikoff, et al., 2009a; Rippetoe & Rogers, 1987; Stanley & Maddux, 1986; Tulloch, et al., 2009; van der Velde, et al., 1996), including Type 2 Diabetes (Plotnikoff,

et al., 2010; Plotnikoff, et al., 2009b). Both PMT meta-analyses showed RE to have a significant positive relationship with intention and behaviour (Floyd, et al., 2000; Milne, et al., 2000). Also important to this research study, prior literature has shown RE to have a significant relationship with attitude and behavioural intention in technology contexts, including anti-spy/malware software (Chenoweth, et al., 2009; Johnston & Warkentin, 2010; Lee & Larsen, 2009) and information system security (Herath & Rao, 2009b; Ifinedo, 2012; Workman, et al., 2008). Therefore it is hypothesized that the more individuals believe that the use of an ePHR will lead to better Type 2 Diabetes self-management, and the ePHR can assist in reducing the health threat posed by their Type 2 Diabetes, the more likely they are to intend to adopt an ePHR.

H1 – A higher level of RE will positively influence ePHR Adoption Intention for chronic disease self-management.

4.3. Self-Efficacy (SE):

This adaptive coping appraisal construct is defined as "an individual's beliefs about whether he or she is able to perform the recommended coping response" (Milne, et al., 2000, p. 109). In this research it is operationalized as the individual's beliefs in their ability to use an ePHR for Type 2 Diabetes self-management. Previous studies have shown SE to have a significant relationship with intentions in health related contexts (Blanchard, et al., 2009; Courneya & Hellsten, 2001; Fruin, et al., 1992; Graham, et al., 2006; Norman, et al., 2003; Plotnikoff & Higginbotham, 2002; Plotnikoff, et al., 2009a; Plotnikoff & Higginbotham, 1998; Rippetoe & Rogers, 1987; Rudman, et al., 1999; Stanley & Maddux, 1986; Tulloch, et al., 2009; van der Velde, et al., 1996; Wurtele & Maddux, 1987), including Type 2 Diabetes (Plotnikoff, et al., 2010; Plotnikoff, et al., 2009b). Other studies have shown significant relationships between SE and actual usage (Claar & Johnson, 2012). Both PMT meta-analyses showed SE to have a significant positive relationship with intention and behaviour (Floyd, et al., 2000; Milne, et al., 2000). Literature also suggests that people with higher levels of SE will be more capable of making changes or self-managing, in that they have the confidence to undertake self-management activities (Dixon, et al., 2009), and the adoption of an ePHR in this research can be considered a self-management activity. Prior

literature has shown SE to have a significant relationship with behavioural intention in technology contexts, including information systems security intention (Herath & Rao, 2009b; Ifinedo, 2012; Vance, et al., 2012; Workman, et al., 2008) and anti-spy/malware software (Johnston & Warkentin, 2010; Lee & Larsen, 2009; Liang & Xue, 2010). Therefore it is hypothesized that the more people believe in their ability to use an ePHR for Type 2 Diabetes self-management, the more likely they are to intend to adopt an ePHR.

H2 – A higher level of SE will positively influence ePHR Adoption Intention for chronic disease self-management.

4.4. Perceived Task Technology Fit (PTTF):

The TTF construct is typically defined as the perception that the technology matches the user's task requirements and the user's abilities (Lin & Huang, 2008). For this research it is operationalized as the perception that the functionalities and capabilities of an ePHR match the requirements of the task of Type 2 Diabetes self-management. This current research therefore follows prior literature naming conventions (Jarupathirun & Zahedi, 2007; Lin & Huang, 2008) and refers to this construct as Perceived Task Technology Fit (PTTF). TTF has been shown to have both significant mediated relationships with intention to adopt/use (Chang, 2008; Kim, et al., 2010; Klopping & McKinney, 2004; Klopping & McKinney, 2006; Kuo & Lee, 2011; Lam, et al., 2007; Lee, et al., 2009; Shih & Chen, 2013; Yen, et al., 2010; Zhang, et al., 2010) as well as significant direct relationships with intention to adopt/use (Klopping & McKinney, 2004; Klopping & McKinney, 2006; Liu & Goodhue, 2012; Shih & Chen, 2013; Yen, et al., 2010). In addition, TTF has been shown to have significant direct relationships with adoption and use (Dishaw & Strong, 1999; Dishaw, et al., 2001; Goodhue, et al., 1997; Larsen, et al., 2009; Strong, et al., 2006; Zhou, et al., 2010). Previous research has successfully shown the combined effects of TTF along with technology self-efficacy, indicating support for the inclusion of these two constructs together in the research model (Strong, et al., 2006). Furthermore, prior research has shown significant direct relationships between PTTF and the use of technology (Lin & Huang, 2008). Therefore it is hypothesized

that individuals with higher perceptions of fit between the task and the technology will be more likely to intend to adopt an ePHR.

H3 – A higher level of PTTF will positively influence ePHR Adoption Intention for chronic disease self-management.

4.5. Response Costs (RC):

This coping appraisal construct is defined as "how costly performing the recommended response will be to the individual" (Milne, et al., 2000, p. 109). In this research, RC is operationalized as the potential costs, (e.g., monetary, time, etc.) incurred by the individual in performing Type 2 Diabetes self-management using an ePHR. Previous studies have shown RC to have significant negative relationships with behavioural intentions in health-related contexts (Chenoweth, et al., 2009; Rudman, et al., 1999). Another study, specifically in the context of Diabetes showed RC to have a significant negative relationship with actual behaviour (Palardy, et al., 1998). Both PMT meta-analyses showed RC to have significant negative relationships with intention and behaviour (Floyd, et al., 2000; Milne, et al., 2000). Also, previous studies have shown RC to have a significant negative relationship with attitude and behavioural intentions in technology contexts including information systems security policy compliance intention (Herath & Rao, 2009b; Vance, et al., 2012), and anti-spy/malware software (Chenoweth, et al., 2009; Lee & Larsen, 2009). Therefore it is hypothesized that individuals will be less likely to intend to adopt an ePHR if they deem the 'costs' to be high.

H4 – A higher level of RC will negatively influence ePHR Adoption Intention for chronic disease self-management.

4.6. Patient Activation Measure (PAM):

PAM is defined as, and is operationalized in this study as a person's beliefs, motivation, knowledge, skills, confidence and actions for health care self-management (Greene & Hibbard, 2012; Mosen, et al., 2007; Remmers, et al., 2009). Previous research has shown PAM to be a validated measure of a person's level of activation and shows that people with higher levels of activation:

- Exhibit more readiness to change and live a healthier lifestyle (Fowles, et al., 2009)
- Report lower levels of difficulty in the management of their chronic disease (Rask, et al., 2009)
- Perceive a more proactive role for themselves in the management of their chronic condition (Dixon, et al., 2009)
- Are more likely to perform self-management behaviours (Rask, et al., 2009) such as monitoring their condition (Hibbard & Cunningham, 2008)
- Exhibit increased use of self-management services and show improved outcomes for performance of self-management behaviours (Mosen, et al., 2007)
- Provide more detail about and suggest a greater number of different coping strategies (Dixon, et al., 2009)

PAM has been shown to provide an assessment of an individual's abilities to manage a complex set of behaviours (Fowles, et al., 2009), and has been shown to be more applicable to personal behaviours (e.g., seeking health information) as compared to group behaviours (e.g., attending classes) (Fowles, et al., 2009). Given that the use of an ePHR can be considered a personal behaviour that assists an individual in the management of the complex set of behaviours required in the self-management of Type 2 Diabetes, PAM is an applicable construct and warrants inclusion in this research model.

While there are no known previous research studies that have studied the relationship between PAM→PTTF or PAM→SE, one noted study (Block & Keller, 1998) examined the relationship between SE and a concept very similar to PAM (i.e., the Transtheoretical Model or TTM that defines five stages that people progress through as they attempt to attain their health goals). That study found a significant and positive relationship between interest in maintaining health related behaviours after taking action (i.e., higher stages in the TTM) and self-efficacy, as well as stronger correlations between higher stages of TTM and self-efficacy. While PAM has similarities to TTM, PAM extends the concepts of TTM to include skills and knowledge acquisition (Hibbard, et al., 2005). In addition, TTM requires the development of a measurement tool specific to the behaviour, whereas PAM can be applied to a variety of contexts without the need to develop a new set of measurement instruments (Hibbard, et al., 2005). Finally, a portion of PAM's focus involves chronic disease (Hibbard, et al., 2005), which makes it

especially suited for this research study. Therefore, based on these factors, PAM was selected as preferable (compared to TTM) for this research study.

A number of logical conclusions from the information provided above support the relationship between PAM→PTTF. First, given the greater readiness to change amongst people reporting higher PAM levels, and the fact that the assessment of the fit between the task of self-management and the ePHR technology requires the ability to accept change and 'think outside the box' with respect to Type 2 Diabetes self-management, it is more likely that people with higher levels of PAM will be able to better see the fit between the self-management task and the ePHR technology. Second, since the use of an ePHR allows the patient to take a more proactive role in the task of self-management, and given that people with higher levels of PAM perceive a more proactive role for themselves in self-management, it is more likely that they will see the fit between the task of self-management and the proactive role that an ePHR can play. Third, given that people with higher levels of PAM are more likely to perform self-management behaviours and show increased use of self-management services, it is more likely that these people would see the fit between the ePHR (which provides self-management services) and the task of self-management, given their propensity to want to perform self-management tasks. Finally, given that people with higher PAM levels suggest more coping strategies (including self-management options), and the use of an ePHR can be considered a coping strategy, it is more likely that people with higher levels of PAM would identify the ePHR as a coping strategy to manage their Type 2 Diabetes and see the fit between the ePHR and the task of self-management. Therefore it is hypothesized that:

H5a – A higher level of PAM will positively influence PTTF.

Similar to the hypothesized relationship between PAM→PTTF, a number of logical conclusions from the PAM research can be drawn for the relationship between PAM→SE. First, people with higher levels of PAM report lower levels of difficulty in management of their Diabetes, and given that an ePHR is a self-management mechanism, it is logical to assume that these people would have less difficulty in using an ePHR to self-manage their Diabetes and therefore report higher levels of self-efficacy in the use of an

ePHR for Type 2 Diabetes self-management. Second, given that people with higher levels of PAM show increased use of self-management services, it is logical to assume that they would exhibit a greater ability to use a self-management tool/service such as an ePHR. Finally, given people with higher levels of PAM are able to provide more details about, and suggest a greater number of coping strategies, it is logical to assume that they would feel more strongly regarding their abilities to learn about and use an ePHR, which can be considered a tool in their Type 2 Diabetes self-management coping strategy. Therefore, it is hypothesized that:

H5b – A higher level of PAM will positively influence SE.

4.7. Severity (SEV) and Vulnerability (VUL):

The SEV threat appraisal construct is defined as "how serious the individual believes that the threat [is] to his or her own life" (Milne, et al., 2000, p. 108). In this research, SEV is operationalized as the perception of how severe the risks posed by Type 2 Diabetes are to the individual's health. The VUL threat appraisal construct is defined as "how personally susceptible an individual feels to the communicated threat" (Milne, et al., 2000, p. 108). In this research, VUL is operationalized as the perception of how susceptible the individual feels to future complications posed by their Type 2 Diabetes (i.e., will they actually become afflicted with the potential negative health complications posed by their Type 2 Diabetes). Typically in PMT studies, SEV and VUL are hypothesized to have direct relationships with behavioural intentions (meta-analyses by Floyd, et al., 2000; Milne, et al., 2000). However, these two meta-analyses indicate that the relationships between SEV/VUL and intentions are not as strong as the relationships between the coping PMT variables (i.e., SE, RE and RC) and intentions. These meta-analyses have shown "The associations between coping variables (efficacy and costs) and persuasion measures (behavioral intention, concurrent behavior, and subsequent behavior) were stronger than the associations between threat variables (vulnerability and severity) and persuasion measures [(behavioral intention, concurrent behavior, and subsequent behavior)]." (Cismaru, et al., 2008, p. 5). A number of previous studies were unable to show that SEV has a significant direct relationship with behavioural

intentions (Blanchard, et al., 2009; Ifinedo, 2012; Norman, et al., 2003). Similarly, a number of previous studies failed to show that VUL has a significant direct relationship with behavioural intentions (Blanchard, et al., 2009; Graham, et al., 2006), including studies in the context of Type 2 Diabetes (Plotnikoff, et al., 2010).

Following the design of OPMT, this study hypothesizes that the SEV and VUL threat variables relationships with intentions are fully mediated by the efficacy variables (i.e. SE, RE and PTTF). Furthermore, it is hypothesized that SEV and VUL will exhibit positive relationships with the efficacy variables, in that people experiencing stronger perceptions about the severity of their Type 2 Diabetes and vulnerability to the complications from their Type 2 Diabetes will report higher responses to the efficacy items. The reasoning for the expected positive relationship is two-fold. First, an examination of PMT studies that reported correlations (e.g., Blanchard, et al., 2009; Chenoweth, et al., 2009; Courneya & Hellsten, 2001; Graham, et al., 2006; Herath & Rao, 2009b; Ifinedo, 2012; Johnston & Warkentin, 2010; Liang & Xue, 2010; Norman, et al., 2003; Palardy, et al., 1998; Plotnikoff, et al., 2010; Plotnikoff, et al., 2009a; Plotnikoff, et al., 2009b; Vance, et al., 2012) between SEV→SE and SEV→RE indicate in the majority of these studies (i.e., 75.8%), the correlations between these variables are positive. Similarly, in the PMT studies (examples noted above) that reported correlations between VUL→SE and VUL→RE, the majority of these studies (i.e., 78.8%) show that the correlations between these variables are positive. Given these positive correlations in previous literature, it is logical to anticipate that these relationships in the model would be positive. Secondly, while a previous study using a model similar to the model in this current research hypothesized negative relationships between SEV→RE, SEV→SE, VUL→RE as well as VUL→SE (Johnston & Warkentin, 2010), the context of that study was anti-spyware software adoption under the threat of a computer becoming infected with spyware. The Johnston and Warkentin (2010) study hypothesized that "As the threat is perceived to be more severe, an end user will feel less able to effectively address the threat." and that "it is expected that perceptions regarding a particular anti-spyware solution to effectively and efficiently provide protection will decrease in strength as the threat of such an attack becomes more probable." (p. 555). Effectively, the Johnston and Warkentin (2010) study

hypothesized a reaction of hopelessness and therefore submission to the threat. In contrast to the Johnston and Warkentin (2010) study, this current ePHR adoption research study argues while 'giving up' may be a reaction in the face of a computer being infected with spyware (where the worst case scenario is the loss of data and potential damage to the computer system), 'giving up' is not a likely reaction when facing the health threats posed by one's Type 2 Diabetes, where the worst case scenario is death. Rather, this research proposes that people contemplating the severity and vulnerability of the threat posed by their Type 2 Diabetes will have the opposite reaction (i.e., seeking solutions that may help them manage the chronic disease), wanting to believe that they will be able to use these solutions, and that these solutions will help. In essence, rather than feelings of 'hopelessness' it is posited that these people will experience feelings of 'hopefulness'. There is much support for this way of thinking in mainstream media. For example, people afflicted with Multiple Sclerosis (MS) cling to hope that Liberation Therapy will assist them with their disease, often travelling internationally to receive the therapy even with conflicting evidence that there are any benefits (Preshaw, 2013). Similarly, people suffering from Chronic Fatigue Syndrome cling to the hope evidence that their affliction is real, and a cause for the affliction has been found, even when the evidence has been refuted (Eveleth, 2012). Medical journals also report on patients and family members clinging to hope with respect to chronic diseases, such as the hope that new medications for curing cancer become available (Ekert, 2013). Finally, studies on chronic illness have shown that "Patients with many types of diagnosis find that hope is an important strategy in coping with their illness" and these patients "described specific cognitive or behavioral strategies used for maintaining hope" (Raleigh, 1992), thus providing evidence that people suffering from chronic disease are more likely to exhibit feelings of hopefulness and seek strategies to help maintain that hopefulness. Therefore it is hypothesized that individuals who believe that the severity of the health threat posed by their Type 2 Diabetes is high will be more likely to believe in their ability to use an ePHR, that the ePHR technology fits the task of Type 2 Diabetes self-management and that the use of en ePHR will lead to better Type 2 Diabetes self-management and positive health outcomes.

H6a – A higher level of SEV will positively influence PTTF.

H6b – A higher level of SEV will positively influence SE.

H6c – A higher level of SEV will positively influence RE.

Similarly, it is hypothesized that individuals who believe that their vulnerability to the health threats posed by their Type 2 Diabetes is high will be more likely to believe in their ability to use an ePHR, that the ePHR technology fits the task of Type 2 Diabetes self-management and that the use of an ePHR will lead to better Type 2 Diabetes self-management and positive health outcomes.

H7a – A higher level of VUL will positively influence PTTF.

H7b – A higher level of VUL will positively influence SE.

H7c – A higher level of VUL will positively influence RE.

4.8. Educational Interventions (EI):

One of the secondary objectives of this study is to determine the effects, if any, that educational interventions have on ePHR adoption. Therefore, this study manipulated the levels of educational interventions experienced by the respondents (randomly assigned to one of four groups in a 2 x 2 matrix, see Table 5, pg. 51), through the use of carefully designed video clips. Specifically, this study examined the roles of Diabetes Complications (DC) education and ePHR education. For the DC education, survey participants either received no complication information/education, or intense (and negatively framed) complication information/education. For ePHR education, participants received either basic ePHR information/education or advanced ePHR information/education.

A number of previous PMT studies have successfully employed negatively framed message educational interventions, with those participants receiving the higher threat messages reporting higher levels of SEV and/or VUL or an overall threat score that combines SEV and VUL. These studies involved health based fear appeal messaging (Brouwers & Sorrentino, 1993; Courneya & Hellsten, 2001; Graham, et al., 2006; McMath & Prentice-Dunn, 2005; Milne, et al., 2002; Prentice-Dunn, et al., 2001; Rippetoe & Rogers, 1987; Wurtele & Maddux, 1987) as well as IS based fear appeal messaging (Johnston

& Warkentin, 2010). Thus, support is provided for the effects of negatively framed educational interventions on the SEV and VUL constructs.

It is hypothesized that those individuals who receive intense (i.e., high threat) versus no DC education (i.e., no threat) are expected to feel that they are more vulnerable to chronic disease complications, and those complications will be more severe, as they received education providing increased awareness of the negative health effects, complications and reduced life expectancy (via unsettling statistics and graphic images) related to their Type 2 Diabetes. Specifically this study hypothesizes that:

H8a – Individuals receiving intense DC education will experience higher perceptions of SEV compared to individuals receiving no DC education.

H8b – Individuals receiving intense DC education will experience higher perceptions of VUL compared to individuals receiving no DC education.

Secondly, individuals receiving advanced ePHR education will gain a greater understanding not only on how to use an ePHR, but also on how an ePHR can help them to effectively self-manage their Type 2 Diabetes and the benefits associated with self-managing via an ePHR. In essence, the ePHR educational intervention involves demonstrating to participants the use of and benefits of using an ePHR for Type 2 Diabetes self-management. Although there are no known previous studies with direct theoretical support for the hypothesized relations between ePHR educational interventions and various efficacy constructs in the model (i.e., RE, PTTF and SE), literature from parallel domains supports the hypothesized relationships. Specifically, in the TAM3 literature (Venkatesh & Bala, 2008) "Training has been suggested as one of the most important post-implementation interventions that leads to greater user acceptance and system success" (p. 299). TAM3 also posits that "training can be used to help users develop favorable perceptions of different determinants of perceived usefulness [PU] and perceived ease of use [PEOU]" (Venkatesh & Bala, 2008, p. 299). Earlier work by Venkatesh (1999) also found that different types of training have effects on PU and PEOU. Given the similarities between training and the advanced ePHR demonstration, combined with the fact that PU is similar to the RE construct, and that

PEOU is similar to SE in this study's research model, it is logical to assume that educational interventions involving an advanced ePHR demonstration will affect the efficacy constructs (i.e., RE, SE and PTTF).

It is hypothesized that participants who receive advanced as opposed to basic PHR education will better understand the benefits, usefulness, ease of use and fit between the ePHR and the task of Type 2 Diabetes self-management, and specifically believe that:

1. The use of an ePHR will lead to better Type 2 Diabetes self-management;
2. Their abilities to use an ePHR are stronger, and;
3. The fit between a PHR and the task Type 2 Diabetes self-management is better.

Based on the above logic and support in the literature, each of the hypotheses related to PHR educational interventions are examined below. First, it is expected that the individuals receiving advanced ePHR education should experience higher levels of response efficacy, as they will have received enhanced education on how the use of an ePHR can help reduce the threats posed by their Type 2 Diabetes, and therefore feel that an ePHR can provide them with the outcomes (i.e., better health, etc.) that they seek. Therefore it is hypothesized that:

H9a – Individuals receiving advanced ePHR education will experience higher perceptions of RE compared to individuals receiving basic ePHR education.

Second, it is expected that the individuals receiving the advanced ePHR education should exhibit stronger self-efficacy, as they will feel more confident in their abilities to use an ePHR for Type 2 Diabetes self-management (as they will have viewed a video clip that demonstrates how to use an ePHR in a real-life Type 2 Diabetes self-management scenario). Therefore it is hypothesized that:

H9b – Individuals receiving advanced ePHR education will experience higher perceptions of SE compared to individuals receiving basic ePHR education.

Finally, it is expected that the individuals receiving advanced ePHR education should be more likely to believe that ePHR technology better fits the task of Type 2 Diabetes self-management, as the education received detailed reasons why an ePHR is well-suited for the task of Type 2 Diabetes self-management (with a real-life scenario demonstration). Therefore it is hypothesized that:

H9c – Individuals receiving advanced ePHR education will experience higher perceptions of PTTF compared to individuals receiving basic ePHR education.

It should be noted that these educational intervention hypotheses are not included in the research model (see Figure 8), as they were analyzed using different methods (i.e., ANOVA, MANOVA), rather than being part of the structural equation model analysis. This follows the methodology as per Nicolaou and McKnight (2006) who "used analysis of variance (ANOVA) to test the experimental effects and partial least squares (PLS) to test the measured part of the research model." (p. 342).

Chapter 5. Research Methodology

5.1. Research Setting and Participant Characteristics

This study focused on the adoption of ePHRs by people with a chronic disease. For the purposes of this research, the chronic disease was operationalized as Type 2 Diabetes and therefore participants were required to be currently diagnosed with Type 2 Diabetes. A number of factors were taken into account when considering this research setting, focus and participant criteria:

1. People with chronic diseases that require a large number of measurements to be recorded are good candidates for benefitting from the use of a PHR (Pope, et al., 2006). People with Type 2 Diabetes typically require a large number of measurements to be recorded (Russell, et al., 2005) and may therefore benefit from measuring and monitoring blood glucose levels, weight, exercise, diet, etc. using an ePHR.
2. Due to the focus on self-management, the selection of the chronic condition should involve one where self-management education objectives are easy to define, and the treatment or intervention response is conducive to self-management programs and education. For Type 2 Diabetes, there are easily defined self-management objectives such as a reduction in blood glucose levels, etc., and self-management has been shown to have an effect on typical Type 2 Diabetes health factors, such as a reduction in blood glucose levels (Chodosh, et al., 2005; Warsi, et al., 2004).
3. Finally, the selection of the chronic disease to be studied should be partially based on the societal impact of the disease. The WHO has indicated that Diabetes will see much higher than average growth rates among the chronic diseases (World Health Organization, 2005), and therefore the societal impact of Diabetes is very high. In addition, given that 90% of people with Diabetes suffer from Type 2 Diabetes (World Health Organization, 2013a) versus Type 1 Diabetes, selecting Type 2 Diabetes for the research setting secured access to a larger pool of potential participants, and ensured the generalizability of this research to a larger audience.

Therefore, participants in this study were required to be adults (age 18+) with Type 2 Diabetes. In addition, participants were required to have limited to no prior knowledge or experience with ePHRs to control for the effects that previous ePHR knowledge may have with respect to the variables in the model. Given prior research has noted that only 7% of people use an ePHR (Archer, et al., 2011), this research is applicable to approximately 93% of the population and therefore not including individuals with strong knowledge and/or use of ePHRs should not bias the results.

5.2. Experimental Procedure

This research study involved a cross-sectional survey conducted online. The survey was created with LimeSurvey, an open-source software survey tool that allows for a large amount of flexibility in programming. Respondents were provided with a link to the survey, and all available methods were used to ensure respondents only answered the survey once. Upon clicking the link, respondents were thanked in advance for their participation in the study, advised of the compensation and instructed that the survey would take approximately 30 minutes. Prior to moving forward with the remainder of the survey, respondents were pre-screened to confirm that they indicated they currently have Type 2 Diabetes, as well as to ensure they had limited or no prior knowledge of ePHRs. Only respondents with Type 2 Diabetes who indicated no knowledge or limited knowledge of ePHRs were allowed to proceed further in the study. In this research, only 1.33% of respondents indicated advanced knowledge (which may have included prior ePHR use), and 13.11% indicated good knowledge (which included a good understanding of ePHRs but not necessarily having used an ePHR). These values are consistent with the research which indicates 7% of people have used an ePHR (Archer, et al., 2011), supporting the conclusion that the research pool is representative of the general population. A roughly equal proportion of respondents (i.e., 118 or 51.3%) indicated no ePHR knowledge, while the remainder (i.e., 112 or 48.7%) indicated limited ePHR knowledge. This screening was done to ensure prior knowledge of ePHRs was controlled for in the study. Respondents were then required to provide their age and gender, in order to ensure that these demographics for the sample closely matched these demographics for the general population with Type 2 Diabetes. Respondents were required to provide consent after viewing the online consent form, which

outlined all of the necessary terms and conditions of the study as per the McMaster Research Ethics Board. The consent form (see Appendix C) warned respondents that they may be exposed to potentially unsettling information about Type 2 Diabetes complications, and also advised them that they could withdraw from the study at any time. After providing consent, respondents were asked a small number of questions regarding their Type 2 Diabetes (i.e., level of control, knowledge, etc.) Respondents were provided with some general information about the survey and instructions to complete the survey (e.g., how to move forward, how to pause/restart the videos, etc.) Also at this time, respondents were given information that stressed the importance of reading the questions carefully, watching the videos in their entirety, and to ensure the volume on their computer was at a level they were able to hear (for the video clips).

Due to the secondary focus of this study on the effects of educational interventions on the adoption of ePHRs, the participants were randomly placed in one of four groups, in a 2 x 2 matrix, as detailed in Table 5. The randomization was completed with computer scripting, and therefore the respondents did not know which group they were in, or the fact that they were being placed in a group at all. Respondents from groups 1 and 2 (i.e., collectively the Diabetes Complication (DC) education control group) were presented with a video clip about the Frederick Banting House Museum in London, Ontario (see Appendix A, Part 1). While this video was related to Diabetes, it did not present any information about Diabetes complications. Respondents from groups 3 and 4 (i.e., collectively the DC education experimental treatment group) were presented with a video clip that outlined intense and negatively framed information about the complications of Type 2 Diabetes, using a combination of graphic images and disturbing yet accurate and objective statistics about health issues and death rates related to Diabetes (see Appendix A, Part 2). Prior literature supports the use of a control group (i.e., groups 1 and 2 who received no Diabetes complication education) versus an experimental group (i.e., groups 3 and 4 who received intense Diabetes complication education). Milne et al. (2000) state that one of the PMT study research designs involves health-education intervention studies, where one group (the experimental

group) receives information about the health threat and the second group (the control group) does not receive this information (Milne, et al., 2000).

Table 5 – Participant Groups

		ePHR Education (ePHR)	
		Basic (i.e., general information about ePHRs and the benefits of using an ePHR)	**Advanced** (i.e., general ePHR information, real-life based example of how an ePHR can be used to self-manage Type 2 Diabetes, benefits of using an ePHR)
Diabetes Complication Education (DC) Education*	**None** (group viewed an unrelated video clip about the Frederick Banting House museum)	**Group 1** • ePHR Education - Basic • Diabetes Complication Education - None	**Group 2** • ePHR Education - Advanced • Diabetes Complication Education - None
	Intense (e.g., life threatening complications such as stroke, kidney failure, blindness, ulcerations, amputations, etc. and death)	**Group 3** • ePHR Education - Basic • Diabetes Complication Education - Intense	**Group 4** • ePHR Education - Advanced • Diabetes Complication Education - Intense

After viewing the first video clip, participants completed responses to the survey items for the SEV and VUL constructs (as these were hypothesized to be affected by the DC educational intervention), followed by completing responses to the manipulation check items for the DC educational intervention. Following these questions, respondents in groups 1 and 3 (i.e., collectively the ePHR education low treatment group) were shown a video clip that provided basic information about ePHRs and their benefits (see Appendix A, Part 3), while respondents in groups 2 and 4 (i.e., collectively the ePHR education high treatment group) were shown a video clip that provided advanced information about the use of ePHRs and benefits, using a real-life based demonstration/simulation of how people with Type 2 Diabetes could self-manage their disease with an ePHR (see Appendix A, Part 4). It should be noted that both the basic and advanced ePHR educational video clips provided similar information about ePHRs and their benefits. However, while the basic video clip simply provided textual bullet points to convey this information, the advanced video clip provided this information using a real-life simulation of the use and benefits of an ePHR, with a fictional yet realistic scenario involving a person who is currently suffering from Type 2 Diabetes. Similar to the DC educational intervention, a standard PMT research design was used for the

ePHR educational intervention. Specifically, as per Milne et al. (2000), in experimental manipulations of specific PMT variables, "particular PMT variables are manipulated (high vs. low) in a communication prior to their measurement." (Milne, et al., 2000, p. 114).

While Appendix A provides screen captures of the video clips to give the reader of this document a sense of what respondents viewed during the survey process, all video clips had voice over narration, which in some cases provided enhancements to the visual content. Voice narration was also deemed important, as many people with Type 2 Diabetes suffer from vision problems, and therefore may not have been able to read some of the smaller text on the screens (although they would have been able to see the much larger images that were presented). Therefore, the voice narration provided the details of what was shown on screen, and/or enhanced details about the content. To fully comprehend the video clip content, Internet URL links to the four video clips are provided below.

- DC=0 (Frederick Banting House Museum, Groups 1 and 2) - http://www.youtube.com/v/2eGMDzRcCKs
- DC=1 (Intense Diabetes Complications, Groups 3 and 4) - http://www.youtube.com/v/yE1QRoMNxZ0
- ePHR=0 (Basic ePHR Education, Groups 1 and 3) - http://www.youtube.com/v/UcpMgzbUwTk
- ePHR=1 (Advanced ePHR Education, Groups 2 and 4) - http://www.youtube.com/v/8L_hWR4uNY4

During the survey process, all attempts were made to ensure that respondents viewed the video clips in their entirety. Specifically, respondents were unable to fast forward the video clips, as the controls for this function were disabled. In addition, a timer was put in place that would not allow respondents to move on to the next screen in the survey process until a valid amount of time (i.e., the length of the video) had passed. It is important to reiterate that respondents viewed the DC video, followed by survey questions regarding the SEV and VUL constructs and manipulation check questions for the DC video clips, and were then presented with the ePHR education video, followed by survey questions regarding the remaining constructs and manipulation check questions regarding the ePHR education video clips. The survey was ordered in this manner to match the flow of OPMT, as described earlier (i.e., Threat followed by Efficacy and Intentions). Previous literature provides support for the presentation of the messages in this specific order, stating that "threatening health information energizes one to act in both

adaptive and maladaptive ways" and "the order of presentation of the information may affect the extent to which people respond adaptively" (Prentice-Dunn, et al., 2001, p. 81).

At the end of the survey, respondents answered a number of demographic and general health questions. Finally, in addition to collecting the quantitative responses for the construct measures and control variables noted above, responses to open-ended questions relating to participant perceptions about ePHRs, self-management and the educational interventions were also collected. Responses to the open-ended questions were analyzed to strengthen the empirical findings through triangulation (Benbasat, et al., 1987), as well as to reveal any insights into unsupported hypotheses.

Respondents from Groups 1 and 3 were provided with an opportunity to watch the Advanced ePHR education video clip at the end of the survey, in order to give them the same ePHR information as respondents in Groups 2 and 4 received regarding the benefits of ePHRs (as per research ethics guidelines). This process occurred after all survey questions had been answered so that responses for respondents in Groups 1 and 3 were not influenced by the Advanced ePHR education video clip. At the end of the survey process, respondents were thanked for their time and provided with contact information for Diabetes organizations (both national and local) they could contact if they felt they needed to (again, as per research ethics guidelines).

While the length of time taken to complete the survey varied depending on the group the participant was placed in (and thus viewing video clips of differing lengths), the average time to complete the survey for all respondents was 34 minutes and 38 seconds, indicating that participants on average appear to have taken an appropriate amount of time to watch their given video clips and carefully read/answer the questions. A copy of all survey questions, in the format and order they appeared in the survey process is included in Appendix D.

Survey responses were completely anonymous, and all answers to the questions were captured electronically and stored on secure McMaster University servers. Daily backups to the data file were made and kept on the researcher's computer that was located in a locked room on the McMaster University campus. All required ethics protocols regarding data privacy and security were followed.

5.3. Research Stages

The research program was completed in three stages, an initial focus group, a pilot study and a main study, as described below.

5.3.1. Focus Group

The research included a single focus group with people previously diagnosed with Type 2 Diabetes as participants. The purpose of the focus group was to refine the PMT measurement instruments and to refine the educational intervention content. Researchers often develop measurement instruments without the consultation of the target audience (Vogt, et al., 2004). While the use of literature reviews is very common and recommended in the generation of survey items, supplementing this through the use of focus groups consisting of individuals knowledgeable in the field is also useful (Nassar-McMillan & Borders, 2002). In addition, it is noted that the use of interaction in focus groups can draw out knowledge and insights that may not materialize without the group interaction (Nassar-McMillan & Borders, 2002). Specifically, Nassar-McMillan and Borders (2002) stated "Initial instrument development, as well as adaptation of existing instruments, for use with different populations necessitates identifying appropriate items for inclusion. Because the populations targeted by these instruments usually represent an excellent resource for obtaining information critical to identifying and selecting items, they sometimes are utilized as such. Engaging these populations as focus group participants can provide an efficient means for the purposes of both item generation and refinement."(Nassar-McMillan & Borders, 2002, p. 2). Also, the use of focus groups for the development of PMT survey items is recommended by Norman et al. (2005) who indicate that the "preferred, alternative is to develop the questionnaire items specifically for the planned study [by] conducting semi-structured interviews with a sample drawn from the target population" (Norman, et al., 2005, p. 99). For this research, the focus group was used for these 'semi-structured interviews'. The use of focus groups in developing and refining measurements instruments is supported in both a health/sensitive issues context (Kelly, et al., 2005; Kendall & Bloomfield, 2005; O'Brien, 1993; Zeller, 2002), as well as studies employing PMT (Plotnikoff & Higginbotham, 2002).

Established processes and procedures (e.g., standard questionnaire, level of moderator involvement, group size, logistics, etc.) for conducting the focus group session were followed based on those recommended by experts on this topic (Fuller, et al., 1993; Morgan, 1996; Nassar-McMillan & Borders, 2002). The decision as to the number of focus group participants followed the published literature on this topic. Specifically, smaller groups are deemed to be more appropriate when dealing with emotional topics, which leads to a high level of participant involvement and gives participants more time to actively discuss a topic on which they are emotionally invested (Morgan, 1996). The four participants for the focus group conducted as part of this study were secured through a local Diabetes support group (i.e., the Hamilton Adult Diabetes Support Group). The focus group session lasted approximately 120 minutes, and participants were compensated with $25. Full ethics approval was secured prior to the initiation of the focus group. The results of the focus group were used in refining certain PMT constructs, as well as the redevelopment of the educational intervention video clips.

5.3.2. Pilot Study

The importance of a pilot and pre-test was indicated by Boudreau et al. (2001), who stated "researchers should pre-test and/or pilot test instruments, attempting to assess as many validities as possible in this process" (pg. 11). This research included a pilot study, consisting of a sample of 50 people (i.e., approximately 20% of the estimated sample size of the main study). The purpose of the pilot study was to test and refine the measurement instruments, as well as an assessment of the educational intervention content (i.e., based on the video clips, do the educational intervention groups clearly understand how an ePHR can assist them in Diabetes self-management, and do they understand the impacts of Diabetes complications). Pilot study participants were recruited from both local Diabetes Education Centres (DEC) as well as through a well-known Diabetes Online Support Group (TuDiabetes - www.tuDiabetes.org). Copies of the flyer and poster used for DEC recruitment are included in Appendices E and F. A copy of the pilot study posting on the TuDiabetes website is included in Appendix G. Pilot study participants were compensated with a $10 gift card. Full ethics approval for both the pilot phase and main study (detailed below) was secured prior to the initiation of the pilot study.

5.3.3. Main Study

After the focus group and pilot study were completed and the measurement instruments and educational intervention content was finalized, the main phase of the research study occurred. For the main study, a cross sectional survey that assessed ePHR Adoption Intention and the relationships between its antecedent constructs (see Figure 8) was completed. All participants in the main study were adults (i.e., 18+ years old) who indicated that they were currently afflicted with Type 2 Diabetes. Again, participants were screened to ensure that those who had previously used a PHR or had strong knowledge about the use of ePHRs were not included in the research, as the study required 'novice' users with limited ePHR knowledge/experience. In addition, quotas for age and gender were enforced to ensure the demographics of the sample closely matched the demographics of the population with Type 2 Diabetes. Main study participants were recruited through a well-known Diabetes Online Support Group (i.e., TuDiabetes - www.tuDiabetes.org). A copy of the main study posting on the TuDiabetes website is included in Appendix H. In addition, to ensure variability in responses (i.e., not all responses came from the same source) and that the demographics of the sample population matched the demographics of the population with Type 2 Diabetes, a research company (i.e., Research Now) was used to secure the necessary remaining participants. A total of 61 participants (i.e., 25.7%) were secured through TuDiabetes, while 176 participants (i.e., 74.3%) were secured through Research Now.

Recommended sample size for studies using PLS as the analysis method (see Section 5.6 for details on PLS) are calculated via the recommendation from Gefen et al. (2000) indicating that the sample size should be 10 times the larger of either the number of items in the most complex construct or the number of paths going into any one individual construct. Given that the PTTF construct has eight items, this study required a minimum sample size of 80 participants. However, based on the educational intervention analyses designed to compare the between group results (detailed in Section 6.4.4 and Section 6.4.5), efforts to recruit 200+ participants (approximately 50+ in each group) was made. Using sample size calculations developed by the G*Power computer application (Faul, et al., 2007), with an $\alpha = .05$, and Power of 0.80 to determine a medium effect size it was determined that a minimum 204

participants were required. In the end, a total of 237 responses were gathered, and based on an outlier analysis (see Section 6.2.2), a total of 230 usable responses were retained. Each group (see Table 6) had a minimum 47 responses, which satisfied the minimum number per group based on the power requirements outlined above.

Some authors have questioned the '10 times' sample size rule of thumb for PLS, noting that this rule does not consider many factors which are known to affect power (Goodhue, et al., 2006). By recruiting 230 participants (when only 80 are required according to the 10 times rule), this study was more than able to satisfy the power recommendations. Based on calculations in Goodhue et al. (2006), PLS analyses where n=200 are able to detect medium effect sizes with a level of power of 98%, thus providing evidence that the sample size of n=230 was more than sufficient.

Table 6 – Group Respondent Sample Size Summary

		ePHR Education		**Total**
		Basic	**Advanced**	
Diabetes Complications Education	**None**	Group 1 (63, 27.4%)	Group 2 (57, 24.8%)	DC=0 (120, 52.2%)
	Intense	Group 3 (63, 27.4%)	Group 4 (47, 20.4%)	DC=1 110 (47.8%)
Total		ePHR=0 (126, 54.8%)	ePHR=1 (104, 45.2%)	230 (100%)*****

** Note: total is less than 237 due to cases removed, as described in the data screening section.*

5.4. Measurement Instruments

Wherever possible, this research study used previously validated instruments to measure constructs in the proposed model, as per guidelines set forth by Boudreau et al. (2001). However, for context-specific PMT constructs, it is preferred to develop/revise the survey items specifically for the study (Norman, et al., 2005). The measurement instruments, along with sources and scales are included in Appendix B, and described in detail below.

1. PHR Adoption Intention was measured using a three item, 7-point Likert scale adapted from the Behavioural Intention items developed in the Unified Theory of Acceptance and Use of Technology (UTAUT) study (Venkatesh, et al., 2003). In the UTAUT study, the Behavioural Intentions items achieved internal consistency reliability scores between .90 and .92 (Venkatesh, et al., 2003). The items were modified slightly to reflect the ePHR technology context, and to eliminate any time-frame from the questions (i.e.,…in the next <n> months), so as to not limit the respondents thinking to a relatively short time frame.
2. Perceived Task Technology Fit (PTTF) was measured using an eight item, 7-point Likert scale adapted from Lin and Huang's (2008) PTTF items. This study explicitly measured the perception that the technology capabilities matched the user's task requirements, thus making it very applicable to this current study. In the Lin and Huang (2008) study, the PTTF items achieved a Cronbach's Alpha (α) reliability score of 0.97. The items were slightly modified to reflect the ePHR technology context, and to ensure that the respondent was reminded that the task in question was self-management of their Type 2 Diabetes.
3. Patient Activation Measure (PAM) was measured with thirteen items taken from the licensed Patient Activation Measures scale created by Hibbard et al. (2005; 2004). The 13 items were not altered in any way from the questions developed by Hibbard in the short version of the PAM questionnaire (Hibbard, et al., 2005). As per guidelines provided by Insignia Heath (the licensor of the PAM questionnaire), the 13 items were used to calculate a raw score which was then used in converting the ordinal question scores of PAM into a 0 – 100 interval scale. Therefore, in the

research model, the PAM construct is represented by this single item converted score, which therefore does not allow a meaningful Composite Reliability value to be created. However, in the development of the long and short versions of the scale, Hibbard et al. (2005; 2004) concluded that the scale was valid, reliable, and that the short (i.e., 13-item) version of the scale had good psychometric properties similar to the original scale.

4. Self-Efficacy (SE) was measured using a four item, 7-point Likert scale adapted from the SE items developed in the Unified Theory of Acceptance and Use of Technology (UTAUT) study (Venkatesh, et al., 2003). The SE items developed in the UTAUT study used earlier validated items from Compeau and Higgins (1995a) as a foundation for the scale. In the UTAUT study, the SE items achieved internal consistency reliability scores between .89 and .90 (Venkatesh, et al., 2003). The items were modified slightly to reflect the ePHR technology context. While the SE construct is part of the PMT model, this research used an adapted technology SE scale, rather than adapting an SE scale from earlier PMT research. This was done as the SE in question for this research is specifically whether or not the respondent felt they could use a technology (e.g., "I believe I could use an ePHR if I only had the built-in help facility for assistance.") rather than a health related SE (e.g., "I am capable of starting and continuing a program of exercise.").
5. The Severity (SEV), Vulnerability (VUL), and Response Efficacy (RE) constructs from PMT were measured using adapted versions of previously validated scales that were then revised during the focus group session and tested during the pilot study. These three constructs were each measured using a 7-point Likert scale, with six items for SEV, four items for VUL, and four items for RE. The SEV, VUL and RE scales were adapted for a Type 2 Diabetes context from scales developed by Norman et al. (2003). While other previous PMT studies focused on Type 2 Diabetes (Plotnikoff, et al., 2010; Plotnikoff, et al., 2009a; Plotnikoff, et al., 2009b), those SEV and VUL scales consisted of single-item measures, which were not deemed to be suitable for this study. The scales in the Norman et al. (2003) study showed good reliabilities, with Cronbach's Alpha (α) values of 0.78 (SEV), 0.89 (VUL) and 0.85 (RE). As discussed previously, it is preferred for PMT

studies to develop/revise the survey items specifically for the study at hand (Norman, et al., 2005). Therefore, the items for the SEV, VUL and RE constructs were adapted for a Type 2 Diabetes and ePHR context based on the feedback gathered from the focus group conducted with people suffering from Type 2 Diabetes, to ensure the most salient thoughts (regarding severity and vulnerability of Type 2 Diabetes and its complications, along with the response efficacy provided by an ePHR for Type 2 Diabetes self-management) were captured.

6. The Response Cost (RC) construct was measured using an adapted version of a previously validated scale that was revised through the focus group session and tested in the pilot study. RC was measured using a four item 7-point Likert scale. Given there are a limited number of PMT studies that include the RC variable, the RC items were adapted (for a Type 2 Diabetes and ePHR context) from a different study (Milne, et al., 2002) than the one used for the SEV, VUL and RE constructs (as that study did not include an RC construct). The RC scale in the Milne at al. (2002) study showed good reliability, with a Cronbach's Alpha (α) value of 0.76. As noted above, it is preferred for PMT studies to develop/revise the survey items specifically for the study (Norman, et al., 2005). Therefore, the items for the RC construct were adapted for a Type 2 Diabetes and ePHR context based on the feedback gathered from the focus group conducted with people suffering from Type 2 Diabetes, to ensure the most salient thoughts regarding the potential costs of using an ePHR for Type 2 Diabetes self-management were captured.

5.5. Educational Intervention Videos

This research used video clips with audio narration to provide the experimental educational manipulations involved in the study. Research has shown that multimedia (i.e., the use of multiple modes of media such as text, audio and graphics) can improve learning in certain situations (Najjar, 1995; Najjar, 1996). A meta-analysis on the effects of the use of video in patient education found that "Video is as good and often more effective than traditional methods of patient education in increasing short-term knowledge" (Gagliano, 1988, p. 785). Given that this current study was not trying to impart long-term knowledge, but rather provide varying levels of immediate knowledge (regarding Diabetes complications

and the use of an ePHR) just prior to respondents answering a set of questions, the use of video in this research was deemed to be the most effective method of providing education. Finally, the use of multimedia video clips ensured that all respondents were given a chance to absorb the necessary knowledge. For those respondents who may have difficulty hearing, the information was provided textually and graphically in the video. For those respondents with vision problems (a noted potential complication of Diabetes), the information was provided via audio, ensuring that even if they could not read the textual information on screen, they could hear it.

Diabetes Complication Video:

In order to convey the necessary information regarding the potential complications of Type 2 Diabetes, the use of video clips was selected as the preferred method of information transfer. As mentioned previously, this study included two different treatments with respect to the DC educational intervention. The control group watched a video clip that was unrelated to Diabetes complications, but was related to Diabetes. This group watched a short video (see Appendix A, Part 1) about the Frederick Banting House Museum (note, Banting was the scientist who discovered insulin, a treatment for Diabetes). It was necessary for the control group to watch a Diabetes related video (rather than not seeing a video at all), as the manipulation check questions asked specifically about the effects the video clip had on their feelings about severity and vulnerability regarding their Type 2 Diabetes.

The experimental group viewed a video clip that contained information regarding the incidence and effects of Type 2 Diabetes (see Appendix A, Part 2). All of the statistics reported in the intense DC educational intervention video were taken from mainstream and academic sources, and were accurately reported. Given the purpose of the educational intervention was to evoke feelings related to the threat of Type 2 Diabetes complications, the use of graphic images (e.g., amputations, stroke rehabilitation, kidney dialysis treatment, hospital emergency departments, coffins, etc.) regarding these complications was deemed necessary. The use of the video clip allowed simultaneous provision of text, audio and these graphic images. In addition, as mentioned previously, the use of multimedia is an excellent way to

convey short-term knowledge, in this case, increasing respondent knowledge regarding Type 2 Diabetes complications.

The DC intense education video clip focused on the negative health effects, as previous studies have shown that negatively framed messages are more persuasive than positively framed messages (Block & Keller, 1995). Previous PMT research (McMath & Prentice-Dunn, 2005) provides support for the use of negative message health educational interventions and the use of graphic images, with the experimental group in that study receiving high threat messages about the death rates and graphic images of skin cancer. In another PMT study (Milne, et al., 2002), negative messages were used with the experimental group receiving high threat messages regarding the "painful and debilitating effects of CHD [Coronary Heart Disease]" (Milne, et al., 2002, p. 169), while the control group were presented with unrelated information.

ePHR Education Video:

In an effort to convey sufficient education regarding the use and benefits of an ePHR that would provide respondents with enough information to make informed assessments regarding ePHR related questions, the use of video clips was necessary. As mentioned previously, respondents viewed either a basic or advanced video clip regarding ePHRs. In the basic video, respondents were provided with simple textual information about ePHRs and their benefits (see Appendix A, Part 3), both visually and via audio (again to ensure that respondents were able to absorb the knowledge being provided). In addition, to make rational decisions regarding ePHRs (e.g., whether they would adopt, etc.), respondents had to be provided with a minimum, basic level of information regarding ePHRs, and video was deemed to be the best way to impart this basic ePHR knowledge.

The advanced ePHR video (see Appendix A, Part 4) used a real-life based scenario of how a person with Type 2 Diabetes could use an ePHR to self-manage their condition. The advanced video clip incorporated text, audio and graphics to convey a sizable amount of details regarding the use and benefits of an ePHR to respondents. Specifically, the graphics were taken from screen captures of an integrated ePHR prototype developed specifically for this research study. While consideration was initially given to

using a currently commercially available ePHR (e.g., www.webmd.com/phr/, OnTrack Diabetes, etc.) rather than a prototype, there were no systems that included all of the ePHR functions and features that this study wished to convey to respondents (e.g., access to lab results, physician appointment scheduling, physician email communication, medication contra-indication analysis, etc.) Therefore, the development of an ePHR prototype allowed for an all-encompassing demonstration of ePHR usage. The use of an ePHR prototype developed by the researcher also eliminated any effects that commercial branding of the ePHR may have on respondents, thus allowing the respondent to focus solely on the functions, features and benefits of a generic ePHR. Finally, allowing respondents to actually use (i.e., 'test-drive') a currently available ePHR could not ensure that all participants received the same amount of education regarding ePHRs (as they would have been free to only look at areas of the ePHR that interested them). By using screen captures from a prototype, this study was able to control for this factor and ensure that all respondents viewing the advanced ePHR video clip were 'on the same page' with regards to their level of ePHR knowledge. Therefore, the development of a prototype web-based ePHR to create the needed screen captures was deemed optimal. As with the other video clips, the use of multiple forms of media (text, audio and graphics) was necessary to ensure all respondents with any physical impairment in hearing or vision were accommodated, and therefore video with audio narration was deemed the optimal solution for provision of ePHR education. There are a number of additional reasons why the use of video was deemed to be ideal for the ePHR education.

1. As stated by Davis et al. (1989) "A key challenge facing 'user acceptance testing' early in the development process is the difficulty of conveying to users in a realistic way what a proposed system will consist of. The 'paper designs' that typify the status of a system at the initial design stage may not be an adequate stimulus for users to form accurate assessments. However, several techniques can be used to overcome this shortcoming. Rapid prototypes, user interface management systems, and videotape mock-ups [emphasis added] are increasingly being used to create realistic 'facades' of what a system will consist of, at a fraction of the cost of building the complete system." (p. 1000). Given this current research is testing a form of user acceptance (i.e., intention to adopt

an ePHR) that required conveying to users a realistic demonstration of potential use of the ePHR system, the use of video was deemed to be the optimal solution.

2. Use of video allows for presentation of the content in a richer format (Raney, et al., 2003) which is a more common method to present product features for commercial systems (Jiang & Benbasat, 2007a) such as an ePHR, where an understanding of features and benefits is important.
3. Use of narrated video clips allows for better consumer understanding of products in terms of product knowledge (Jiang & Benbasat, 2007b) and greater ability to recall information as compared to static text (Li, et al., 2012). Evidence shows that multimedia learning is most effective when "The media are presented to learners with low prior knowledge or aptitude in the domain being learned." (Najjar, 1995, p. 10). Given respondents had limited to no ePHR knowledge prior to participating in this research study, the need to impart adequate knowledge in a short period of time, while ensuring respondents could recall and make use of that knowledge when answering the survey questions was imperative, making the use of video clips necessary.
4. The Gagliano (1988) meta-analysis found that role-modeling video increased both knowledge and coping ability. The advanced ePHR video education used a form of role-modeling, in that it incorporated a real-life scenario of how an individual with Type 2 Diabetes could use an ePHR to self-manage their disease, effectively allowing the respondent watching the video to imagine they were in the role of the person using the ePHR, and how the ePHR may help them cope with their disease.
5. Previous IS research (Compeau & Higgins, 1995b; Mun & Davis, 2003) provides evidence to show the benefits of using video for software training. Given an ePHR can be considered software, the use of video is well justified in educating respondents on how they could use an ePHR.

The basic ePHR education video provided similar information to the advanced ePHR education video, but the information provided in the basic video was text and audio only, and did not contain any graphics or demonstration of ePHR features/benefits. For example, both the basic and advanced video related to respondents that they could schedule an appointment with their physician through the ePHR, but the advanced video showed a demonstration to the user of how it could be done, the ease of

completing this process, and how to send additional information such as a blood glucose reading chart along with the appointment request.

5.6. Structural Equation Modeling

This research used the second-generation statistical technique of structural equation modeling (SEM). As described by Gefen et al. (2000), "the intricate causal networks enabled by SEM characterize real-world processes better than simple correlation-based models. Therefore, SEM is more suited for the mathematical modeling of complex processes to serve both theory ... and practice" (Gefen, et al., 2000, pg. 4). Many research studies employing PMT (particularly earlier studies) utilized only first generation tools such as ANOVA, MANOVA, regression and in some cases, simple correlation analysis. Therefore, it is beneficial to use the more advanced techniques enabled by SEM to fully explore the power of PMT and its combination with IS theory (i.e., TTF) and PAM.

Once SEM was selected as the statistical technique, the decision as to the specific method (i.e., covariance-based versus component-based) was made. Each method has its advantages and disadvantages. This research used PLS (implemented via Smart-PLS software, version 2.0.M3) for a number of reasons (as per Chin (2010)) which are outlined in Table 7. Prior to completing the SEM analysis, this research study ensured that all pre-analyses with respect to data screening (i.e., missing data, outliers and multivariate statistical assumptions) were completed based on well-known statistical methods (Hair, et al., 2010a; 2010b; Meyers, et al., 2006; Tabachnick & Fidell, 2006). Once the data screening process was complete, an SEM analysis comprising of both examination and assessment of the measurement and structural models, as well as additional analyses (i.e., common method bias, post-hoc) was completed. A summary of the type of analyses, method(s) used and sources is provided in Table 8. From a general perspective, the SEM analysis followed the guidelines set forth by a number of SEM and PLS experts (Chin, 2010; Götz, et al., 2010; Hair, et al., 2011; Hair, et al., 2012; Petter, et al., 2007; Roldán & Sánchez-Franco, 2012).

Table 7 – PLS Justification Summary

Issue/Reason	Description and Study Justification	Applies to this Study
Soft Distributional Assumptions	"PLS makes no distributional assumptions other than predictor specification; PLS avoids the assumptions that observations follow a specific distributional pattern and that they must be independently distributed." • This research had some slight violations of distributional assumptions in the data. Therefore PLS is the preferred method of SEM analysis.	✓
Exploratory in Nature	CBSEM preferable for confirmatory research, component-based methods such as PLS are more suited to exploratory research (Gefen, et al., 2000). • This is first known study to combine PMT with TTF. In addition, this is the first known study to hypothesize and study relationships between PAM and TTF as well as PAM and PMT variables. Therefore, this research can be considered exploratory and thus PLS is the preferred method of SEM analysis.	✓
High Model Complexity	PLS "comes to the fore relative to CBSEM [Covariance Based SEM]" for models of higher complexity. • This research model contains 8 latent variables and 46 manifest variables, compared to average SEM study which contains 4.4 latent variables and 14 manifest variables. Therefore PLS is the preferred method of SEM analysis.	✓
Sample Size Requirement	Sample size requirements for PLS smaller than required for CBSEM • Overall the sample size (i.e., 230) for this research is sufficient for CBSEM, however sub-populations (i.e., based on age, gender, treatment groups, etc.) are smaller than required for CBSEM. Therefore PLS is the preferred method of SEM analysis.	✓
Accuracy of Parameters Estimation	PLS can provide loadings and paths similar to CBSEM without distributional assumptions. • This research had some slight violations of distributional assumptions in the data. Therefore PLS is the preferred method of SEM analysis.	✓
Formative Measurement Items	Modeling formative indicators with PLS is "much less problematic". • A comprehensive examination of the measurement items for the constructs in the model indicates that all constructs are reflective except for Response Costs. • This construct is formative, based on the decision rules outlined by Petter et al. (2007), as detailed in this study (Section 6.4.1– Formative Constructs). • Presence of a single formative construct makes the model a formative one as per Petter et al. (2007) "…once a researcher identifies one or more constructs in the model as formative, the research model must now be considered formative" (p. 640). • Therefore PLS is the preferred method of SEM analysis.	✓
Eschewing the "True" Model for Prediction Focus	PLS more applicable when focus is to make prediction rather than CBSEM which theorizes that "a useful model must fit the data well and make sense scientifically". • The main research objective of this study is to understand how the PMT, PTTF and PAM variables influence (i.e., predict) ePHR adoption. Therefore PLS is the preferred method of SEM analysis.	✓

(Note: unless otherwise referenced, information/quotations in this table have been drawn from Chin, 2010, pp. 656-669)*

Table 8 – SEM Analysis Summary

Analysis Type	Method	Source(s)
Measurement Model – Reflective Constructs:		
Convergent/Discriminant Validity	• Indicator loadings • Indicator cross-loadings	(Gefen & Straub, 2005) (Fornell & Larcker, 1981)
Content Validity	• Literature Reviews • Expert Panels	(Straub, et al., 2004)
Indicator Reliability	• Indicator Loading Significance	(Götz, et al., 2010) (Fornell & Larcker, 1981)
Construct Reliability	• Composite Reliability • Cronbach's Alpha (α)	(Götz, et al., 2010) (Fornell & Larcker, 1981) (Hair, et al., 2010b) (Cronbach, 1951)
Construct Validity	• Average Variance Extracted (AVE) • AVE vs. squared correlations	(Straub, et al., 2004) (Götz, et al., 2010) (Fornell & Larcker, 1981)
Measurement Model – Formative Constructs:		
Construct Validity	• Indicator weights	(Petter, et al., 2007) (Lohmoller, 1989)
Construct Reliability	• Inter-item correlations • Tolerance values • Variance Inflation Factor (VIF)	(Petter, et al., 2007)
External Validity	• Multiple Indicator, Multiple Construct (MIMIC)	(Diamantopoulos & Winklhofer, 2001)
Multicollinearity		
Multicollinearity	• Bivariate correlations • Variance Inflation Factor (VIF)	(Hair, et al., 2010b) (Meyers, et al., 2006)
Common Method Bias:		
Common Method Bias	• Harman's One-Factor Test • Unmeasured Latent Marker Construct (ULMC)	(Podsakoff, et al., 2003) (Liang, et al., 2007)
Structural Model:		
Variance Explained	• R^2 of dependent variables	(Chin, 2010) (Roldán & Sánchez-Franco, 2012) (Petter, et al., 2007)
Path Estimates	• Path Coefficients • Path Coefficient Significance (bootstrapping)	(Chin, 2010) (Roldán & Sánchez-Franco, 2012) (Petter, et al., 2007)
Effect Sizes	• f-test of changes in R^2	(Chin, 2010) (Roldán & Sánchez-Franco, 2012)
Goodness of Fit	• *GoF* Index • Relative *GoF* Index	(Tenenhaus, et al., 2004) (Vinzi, et al., 2010b) (Henseler & Sarstedt, 2012)

Given that a secondary focus of this study is on the impact of the different educational intervention treatments that were introduced to respondents, an analysis of the effects these educational interventions have on specific variables and in the model was completed. The educational intervention analyses included ANOVA and MANOVA statistics.

Finally, in addition to the main study data analyses, a number of post-hoc analyses were also conducted:

1. A detailed comparison of the four individual educational intervention groups (as per the 2 x 2 matrix) was completed using ANOVA analysis methods.
2. An examination of an alternative model containing non-hypothesized relationships was completed. By examining this alternative model, potential significant relationships in the model can be discovered and potential future theoretical contributions can be made.
3. Additional ANOVA and MANOVA analyses were performed to examine effects of the control variables (i.e., demographic, socio-economic, Type 2 Diabetes specific and general health) that were captured in the study. For example, this analysis could indicate if there are significant differences between age groups with respect to the intention to adopt an ePHR.

5.7. Manipulation Validation

In studies involving manipulations (such as the educational interventions used in this study), manipulation validation is required as per Boudreau et al. (2001) who state "manipulation checks are designed to ensure that subjects have, indeed, been manipulated as intended, a validity that can be empirically determined" (Boudreau, et al., 2001, p. 5). Therefore the necessary methods to ensure that the manipulations in this study (i.e., educational interventions) had 'taken' were used. For DC manipulation, a set of questions concerning the perceptions participants had regarding whether or not the video clip increased their feelings of severity, vulnerability and concern about the health threats posed by their Type 2 Diabetes were used (see Appendix D, question 11). These questions assessed participants' perceptions of the intensity of the DC education after experiencing the control video (i.e., Banting Museum video clip) or the intense DC education video clip. The manipulation questions were asked after participants

had responded to the SEV and VUL construct items to eliminate inducing any demand effect as per Nicolaou and McKnight (2006). Similarly, for ePHR education manipulation, a set of questions were used to assess the participants' perceptions regarding whether or not the video clip improved their understanding of how to use an ePHR for Type 2 Diabetes self-management, the benefits of using an ePHR for Type 2 Diabetes self-management and if the video clip increased their confidence in their abilities to use an ePHR for Type 2 Diabetes self-management (see Appendix D, question 18). These questions were asked after the participant was presented with either the basic or advanced ePHR education video clip and after participants had provided responses to the remaining construct items, again to avoid inducing demand effect as per Nicolaou and McKnight (2006). The use of specific manipulation check questions was supported through prior research (Bies & Shapiro, 1987; Johnston & Warkentin, 2010; Nicolaou & McKnight, 2006; Yi, et al., 2013), including studies in a health related context with negatively framed messages (Maheswaran & Meyers-Levy, 1990).

In order to assess the impacts of the educational interventions and manipulations, a number of statistical methods were employed. First, ANOVAs were used to assess the group differences between the responses to the manipulation check questions (Nicolaou & McKnight, 2006; Yi, et al., 2013). Second, both ANOVAs and where applicable MANOVAs were used to assess the group differences between the responses to the items for the constructs that the educational interventions were intended to influence as per previous PMT research involving manipulations (Brouwers & Sorrentino, 1993; Courneya & Hellsten, 2001; Fruin, et al., 1992; Johnston & Warkentin, 2010; McMath & Prentice-Dunn, 2005; Milne, et al., 2002; Prentice-Dunn, et al., 2001; Rippetoe & Rogers, 1987; Stanley & Maddux, 1986; Wurtele & Maddux, 1987).

Chapter 6. Data Analysis and Results

6.1 Data Collection

Data collection occurred in both the pilot study phase and the main study phase, as outlined below.

6.1.1 Pilot Study

Data collection for the pilot study was completed via two methods. Participants for the pilot study were all recruited in July 2012. First, participants were recruited through Diabetes Education Centres (DECs) in Southwestern Ontario. In addition, pilot study participants were recruited through an online Diabetes support group, specifically www.tuDiabetes.org, a well-known support group operated by the Diabetes Hands Foundation. A short description of the study and compensation along with a link to the online survey was posted in July 2012. In total, five participants were recruited through the DECs while 45 participants were recruited through the online support group for a total of 50 pilot participants. All recruitment protocols were followed and participants were required to electronically approve consent prior to completing the survey process.

6.1.2 Main Study

For the main study, data collection was completed via two methods in order to secure sample participants whose demographic profile (i.e., age and gender) matched that of the overall population of people with Type 2 Diabetes. First, participants were once again recruited through the online support group (www.tuDiabetes.org). This recruitment process started on November 14, 2012. Due to slow initial recruitment numbers, the compensation method for the study was changed (i.e., from a random draw for larger value gift card prizes to a $10 gift card for every participant[2]) on November 20, 2012. A total of 61 participants were recruited through the online support group between November 14, 2012 and November 22, 2012. All recruitment protocols were followed and participants were required to electronically approve consent prior to completing the survey process. Secondly, in an effort to ensure a

[2] The change in compensation method occurred after the first 5 participants had been recruited. These participants were promptly notified of the change and all agreed to the new compensation method.

representative sample, both from a demographic standpoint and to ensure variability in respondents (i.e., that all respondents did not come from the same online source), a research organization was hired to recruit the remaining participants. Research Now, a well-known international research firm was contracted to provide the remaining required participants. A total of 176 participants were recruited through Research Now between December 12 and December 21, 2012. Quotas to ensure a representative sample from a demographic standpoint (i.e., age and gender) were incorporated into the survey process. The use of a research firm received full ethics approval prior to the recruitment of any participants through this method. All recruitment protocols were followed and participants were required to electronically approve consent prior to completing the survey process. Compensation for participants recruited through Research Now was completed by that organization. However the researcher ensured that the compensation method received ethics approval.

6.2 Data Screening

Prior to completing statistical analyses, a thorough screening of the data was performed. This data screening included an examination of missing values, outliers (i.e., both univariate and multivariate) as well as multivariate statistical assumptions (i.e., normality, linearity and homoscedasticity). All data screening analyses were completed via SPSS Statistics version 20. A summary of all variable names with descriptions are included in Appendix I.

6.2.1 Missing Values

From the 237 responses gathered from participants, a missing values analysis was completed. There were no missing values identified from the construct item indicator variables. However, there were a limited number of missing variables in the control questions. Given there are no missing variables in the model/construct indicator items, all further statistical analyses that utilize these variables were completed using the data gathered. For missing data in the control variables, the decision to complete mean substitution (or mean imputation) as the method for missing data values was made. Mean substitution

involves replacing missing values for a variable with the overall mean of that variable from all cases and is considered to be the most common and conservative imputation approach (Meyers, et al., 2006). The rationale for mean substitution is based on the fact that "the sample mean is the best estimate of the population mean" (Meyers, et al., 2006, p. 62). Hair et al. (2010b) recommends mean substitution when there are relatively low levels of missing data. Given that the control variables used in the data analysis contain a limited amount of missing data, mean substitution is an acceptable method.

6.2.2 Outlier Analysis

Outliers are "cases with extreme or unusual values on a single variable (univariate) or on a combination of variables (multivariate)" (Meyers, et al., 2006, p. 65). For the purposes of detecting univariate outliers, this analysis uses methods drawn from Cohen (1996) as described in Meyers et al. (2006), specifically 'boxplots'. Boxplots, which are based on median rather than mean scores, are very useful in conveying a number of items of information, including distribution of values, skew, and outliers (Meyers, et al., 2006). The upper and lower 'fences' of the boxplot (i.e., the lines extending from the boxes in Appendix J) are set at 1.5 times the Inter-Quartile Range (IQR), with the IQR being the span of scores between the first and third quartiles of the data. Values outside of the upper and lower 'fences' are considered potential univariate outliers (Meyers, et al., 2006). The boxplot univariate outlier analysis was completed for composite scores created from individual item indicators for all reflective constructs. Composite scores reflect the respondent's score on all of the construct indicator items, and are usually calculated as a mean or a sum (Tinsley & Brown, 2000). These composite scores were used in the univariate outlier analysis to reduce the effects that outliers on any one indicator would have. Given the characteristics of reflective constructs (i.e., indicators are manifestations of the construct, indicators are interchangeable, indicators share a common theme, indicators covary with one another (Petter, et al., 2007)), using composite scores rather than individual indicators for the univariate outlier assessment is warranted. As these boxplots indicate (see Appendix J), there are a small number of univariate outliers for the reflective constructs in the research model.

In addition, separate boxplots for the individual indicators of the lone formative construct in the model is included in Appendix J. Composite scores do not accurately reflect a summary of the individual indicator values for the formative construct (i.e., RC), as formative construct indicators conceptually define the construct (Hardin, et al., 2011), and the indicators do not need to have the same content or share a common theme (Petter, et al., 2007). Therefore, the univariate outlier analysis was performed on the individual formative construct indicator items rather than a composite score. This analysis revealed no univariate outliers for the RC construct indicators. Overall, a total of 18 unique cases with univariate outliers were identified, representing 7.59% of cases. On an individual construct/indicator level, no construct/indicator included more than 3.38% of cases with univariate outliers. A summary of the cases determined to contain potential univariate outliers is included below in Table 9.

Table 9 – Univariate Outlier Summary

Construct/ Indicator	Outlier Case ID Numbers[1,2]	# of Outliers	# of New Outliers	% of Cases with Outliers
SEV	162, 353, 398, 922, 1008, 1081	6	6	2.53%
VUL	353, 436, 454, 553, 588, 697, 871, 922	8	6	3.38%
ADOPT	358, 424, 731, 968	4	4	1.69%
RE	358, 424, 436, 619, 731, 871, 968, 1081	8	1	3.38%
PTTF	424, 731, 879, 968	4	1	1.69%
SE	162, 454, 619, 968	4	0	1.69%
PAM	none	0	0	0.00%
RC1-RC4	none	0	0	0.00%
		TOTAL	**18**	7.59%

1. *Case ID numbers do not correspond to participant numbers*
2. *Items grayed out indicate case ID numbers already identified as an outlier from one of the constructs above it.*

Multivariate outliers are cases with extreme or unusual values on a combination of the variables contained in the model (Meyers, et al., 2006). For multivariate outlier analysis, both Mahalanobis distance as well as Cook's distance statistics were examined. Using SPSS Statistics, a linear regression using case identification (id) numbers as the dependent variable, and SEV, VUL, ADOPT, RE, PTTF, SE, RC1-RC4 and PAM as the independent variables was completed. The Mahalanobis distances were then

compared to a chi-square distribution (X^2) value of 29.588, based on 10 degrees of freedom (calculated as the number of independent variables – 1) and the strict p-value of .001. This analysis indicated that cases 162, 413, 424, 436, 731, 879, 922, 1008 and 1056 could be considered multivariate outliers. However, seven of these nine cases were also identified in the univariate outlier analysis above, leaving only cases 413 and 1056 as newly identified outliers. In addition to the Mahalanobis distance analysis for multivariate outliers, a second method, notably Cook's distance (Di) was used to identify cases with potential multivariate outliers. Authors disagree on a Di cut-off threshold for declaring cases as influential (i.e., outliers), with some arguing Di > 1 (Chatterjee & Hadi, 2006), others arguing for Di > 4/n where n = number of cases (Fox & Long, 1990), Di > 4/(n-k-1) where n = total number of cases in the sample and k = number of predictors (Hair, et al., 2010a), and Di > "the 50% point of the F distribution with p+1 and (n–p–1) degrees of freedom" (Chatterjee & Hadi, 2006, p. 104). None of the cases in the study would be considered outliers based on the Di > 1 or the Di > Fp,n-p (0.5) cut-off thresholds (note that Fp,n-p-1 (0.5) calculation is 0.9479 where p = 12 and n – p – 1 = 224). The Di > 4/n and Di > 4/(n – k – 1) cut-off thresholds are considered to be conservative measures for either small samples or large data sets (Hair, et al., 2010a), and therefore their use was not considered optimal for this mid-sized dataset. Chatterjee and Hadi (2006) recommend that in addition to using rigid cut-off rules, a graphical examination via a dot plot can be useful in identifying outliers (see Figure 9). This visual analysis revealed two cases which should be considered as outliers (note these two cases have been circled in Figure 9). These two cases are 162 and 922. However, both of these cases were identified in the earlier univariate and Mahalanobis distance outlier analysis, indicating no additional newly identified outliers.

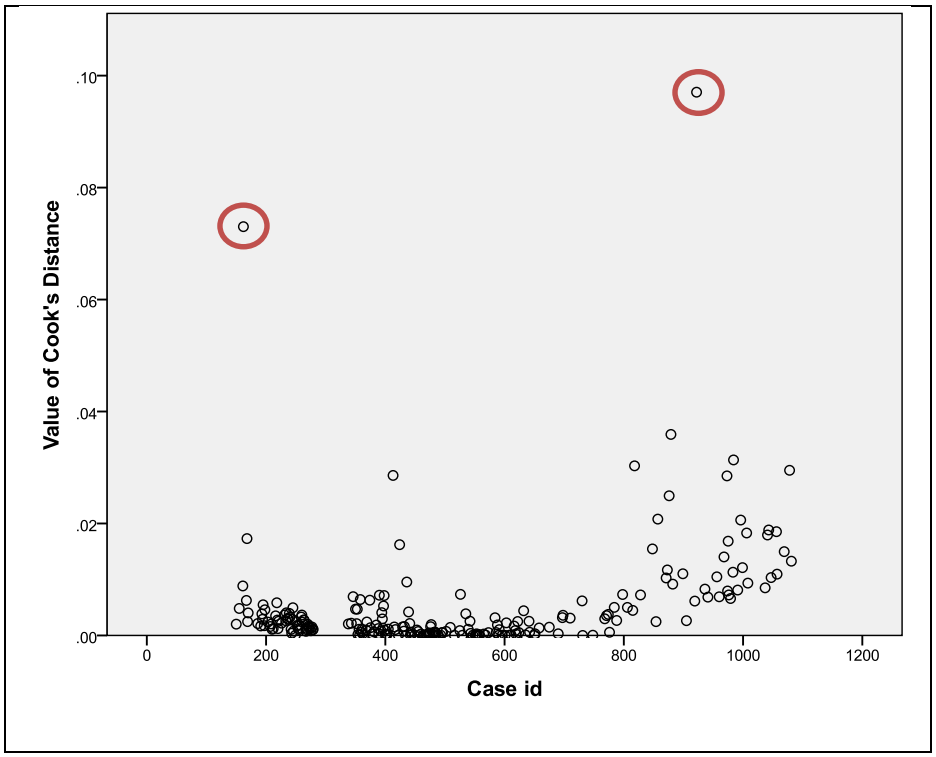


Figure 9 – Cook's Distance Dot Plot

In total the outlier analysis identified 18 unique cases with univariate and/or multivariate outliers and two unique cases with only multivariate outliers, for a total of 20 unique cases with potential outlier issues. Once outliers have been identified, the decision needs to be made regarding the removal or inclusion of the cases containing the outlier issues. Meyers et al. (2006) note four reasons why there may be outliers in a data set: data entry errors; functions of extraordinary events or unusual circumstances; outliers with no explanation, and; multivariate outliers where the uniqueness lies in the combination of the variables. The data set was fully checked for data errors (note there could be no researcher data transcription entry errors in this study, as responses were gathered online and saved immediately and directly to a data file). There is no reason to suspect that any extraordinary events or unusual circumstances played a role during the collection of this data, and therefore that outlier reason does not apply to this data set. Therefore, it is assumed that the outliers in this data set are either those with no explanation or those exhibiting multivariate outlier issues. By cross-referencing the univariate and multivariate list of outliers, seven cases were identified with multivariate outlier issues (via both the

Cook's distance and Mahalanobis distance measures) and also identified with univariate outlier issues and were therefore selected for removal. Five of these seven cases had multiple instances (i.e., more than one variable) of univariate outlier issues. Therefore, seven cases (i.e., 162, 424, 436, 731, 879, 922, 1008) were removed from the data set. There are differing philosophies regarding the retention or deletion of outliers (Hair, et al., 2010b). Some authors note that removal of outliers may not ensure generalizability to the entire audience (Hair, et al., 2010b), while others note that inclusion of outliers may lead to results that "do not generalize except to another sample with the same kind of outlier" (Tabachnick & Fidell, 2006, p. 73). The seven cases removed represent only 2.95% of all cases, which can be considered an acceptable amount. This left 230 usable cases in the final data set. Unless otherwise noted, the remaining analysis uses these 230 cases. Previous PMT research (Tulloch, et al., 2009) supports the removal of a small number of cases with univariate and multivariate outlier issues.

6.2.3 Multivariate Statistical Assumptions

A number of statistical assumptions are of significance to multivariate analyses such as SEM (Meyers, et al., 2006). Specifically, the statistical assumptions of normality, linearity and homoscedasticity should be examined, as "should one or more of these assumptions be violated, then the statistical results may become biased or distorted" (Meyers, et al., 2006, p. 67).

Normality

An examination of normality involves a number of statistical analyses, including the statistical approaches of skewness (the symmetry of the distribution), kurtosis (the peakedness of the distribution), statistical tests such as the Shapiro-Wilk test, as well as graphical approaches by examining histograms and normal probability plots (Meyers, et al., 2006). Skewness and kurtosis values for each of the construct items are included in Table 10. For all but one of the construct/indicators (i.e., RC2), the skewness values are negative, meaning that the left tail is longer and that the mass of the distribution can be found on the right side of the figure. This is not wholly unexpected, as the means (see Tables 18 and 22) for most of these indicators were above the midpoint (i.e., 4), yet there were a number of cases where

respondents noted low (i.e., 1) scores. For example, while the mean SEV score was over 5 (indicating the majority of respondents feelings of SEV were on the high side), there were some respondents who reported feeling virtually no feelings of SEV regarding their disease. Different 'rules of thumb' regarding threshold values as indications of skewness non-normality have been put forth, with a common threshold value of ±1.0 (Meyers, et al., 2006). Based on this rule-of-thumb, none of the construct/indicators would be considered skewed. Both Tabachnick and Fidell (2001) and Hair et al. (2010b) also suggest the calculation of z-scores for skewness values. Using a strict critical value of 2.58 (i.e., .01 significance level), z-scores above this value indicate the potential that the distribution is skewed in terms of that construct (Hair, et al., 2010b). Based on this analysis, SEV, VUL, ADOPT, RE, PTTF and SE may be considered to exhibit the non-normality characteristic of skewness.

An examination of the kurtosis analysis results reveals that six (i.e., SEV, VUL, ADOPT, PTTF and SE) of the construct/indicators exhibit positive kurtosis (or leptokurtic), while six of the construct/indicators (RE, PAM and RC1 to RC4) exhibit negative kurtosis (or platykurtic). The same analysis process that was completed for skewness was completed for kurtosis, as per Meyers et al. (2006). In this data none of the constructs exhibit issues with kurtosis at the ±1.0 threshold. Completing the analysis of z-scores as above, none of the construct/indicators exhibit issues with kurtosis, using a critical value of 2.58 (i.e., .01 significance level). In summary, formal statistical methods indicate possible skewness issues with some construct/indicators, but no issues with any of the construct/indicators with respect to kurtosis. However, given normality is not always required for analysis (Tabachnick & Fidell, 2006), sample sizes greater than 200 diminish the effects of non-normality (Hair, et al., 2010b) and PLS is robust to deviations from normality (Chin, 2010; Chin, 1998), the potential skewness of the few noted variables is not an issue.

Table 10 – Data Skewness and Kurtosis

	SEV	VUL	ADOPT	RE	PTTF	SE	PAM	RC1	RC2	RC3	RC4
Mean	5.072	5.370	5.297	5.438	5.358	5.171	70.061	3.87	3.93	4.59	4.17
Median	5.25	5.5	5.667	5.5	5.625	5.25	70.8	4	4	4	4
Mode	6	6	6	6	6	5	82.8	4	5	4	4
Skewness	-.708	-.628	-.770	-.417	-.597	-.557	-.066	-.277	.107	-.127	-.222
Skewness z-score	**-4.425**	**-3.925**	**-4.813**	**-2.606**	**-3.731**	**-3.481**	-.413	-1.731	.669	-.794	-1.388
Kurtosis	.627	.193	.459	-.258	.155	.643	-.544	-.797	-.763	-.235	-.158
Kurtosis z-score	1.959	.603	1.434	-.806	.484	2.009	-1.7	-2.491	-2.384	.-734	-.494

In addition to examining skewness and kurtosis, other statistical tests (i.e., Kolmogorov–Smirnov test, Shapiro-Wilk test) can be used to detect non-normalities in data (Meyers, et al., 2006). The Kolmogorov–Smirnov test has been shown to be less powerful than the Shapiro-Wilk test (Stephens, 1974) and in addition, the Kolmogorov–Smirnov test is best suited for sample sizes that exceed 2,000 (SAS_Institute, 2009). For sample sizes less than 2,000, the Shapiro-Wilk test is recommended (SAS_Institute, 2008a; 2008b). Table 11 details the statistical test values for the Shapiro-Wilk test. To assess possible violations of univariate normality, constructs with significance levels <0.001 could be considered to contain normality issues. For this data, all construct/indicators appear to contain possible deviations from normality, as the significance levels are all <.001 for the Shapiro-Wilk test. However, there are noted limitations to the Shapiro-Wilk test. First, while the test may indicate deviations from normality, it is unable to identify what those deviations are. In this current research dataset, it has been identified that there may be skewness issues with some of the constructs, which may result in the Shapiro-Wilk results. In addition, with larger sample sizes, even slight deviations from normality may produce a significant Shapiro-Wilk test result (Field, et al., 2012). Therefore, a graphical analysis of the data was completed.

Table 11 – Shapiro-Wilk Test of Normality

	Statistic	df	Sig.
SEV	.963	230	.000
VUL	.957	230	.000
ADOPT	.933	230	.000
RE	.965	230	.000
PTTF	.957	230	.000
SE	.969	230	.000
PAM	.972	230	.000
RC1	.931	230	.000
RC2	.940	230	.000
RC3	.935	230	.000
RC4	.937	230	.000

a. Lilliefors Significance Correction

In larger samples (i.e., greater than 200), for data normality Tabachnick and Fidell (2001) suggest the inspection of "the shape of the distribution instead of using formal inference because the equations for standard error of both skewness and kurtosis contain N, and normality is likely to be rejected with large samples even when the deviation is slight" (p. 44). Therefore, graphical approaches to analyze normality including histograms and Q-Q plots have been used in this research. Appendix K contains histograms with the normal distribution curve overlaid to allow a visual examination of normality. As the images shown in Appendix K indicate, it would appear that the data set achieves a sufficient level of normality.

Stevens (2002) suggests normal probability plots (or Q-Q plots) as a more precise method for graphically examining normality. In Q-Q plots, normality is assumed if the data points fall on or near a normal distribution diagonal line that extends from the lower left to the upper right of the chart. Tabachnick and Fidell (2006) also discuss the helpfulness of both expected normality probability plots, as well as detrended expected normal probability plots. In these detrended plots, normality is assumed when "cases distribute themselves evenly above and below the horizontal line that intersects the Y axis at 0, the line of zero deviation from expected normal values" (Tabachnick & Fidell, 2006, p. 81). Both these types of graphs have been included in Appendix L for all constructs/indicators, and indicate that this data set exhibits a sufficient level of normality.

In summary, while there are potential minor indications of non-normality of the data set, much of the analysis indicates only relatively small departures from normality. In addition, Tabachnick and Fidell (2006) state "normality of the variables is not always required for analysis" (p. 79), while Hair et al. (2010b) indicate larger sample sizes diminish the negative effects of non-normality, and that with sample sizes greater than 200, these effects may be negligible and the researcher may not need to be as concerned about non-normal variables. Finally, given that PLS is robust to deviations from normality (Chin, 2010), the current data set was deemed suitable for further statistical analysis.

Linearity

An additional test for fundamental statistical assumptions involves testing the key relationships for linearity. Hair et al. (2010b) stated "An implicit assumption of all multivariate techniques based on correlational measures of association, including multiple regression, logistic regression, factor analysis, and structural equation modeling, is linearity." (p. 76). Both Meyers et al. (2006) and Hair et al. (2010b) recommend the use of bivariate scatterplots as well as a simple regression analysis focusing on an examination of the residuals for assessing linearity. As per Meyers et al. (2006) "Variables that are both normally distributed and linearly related to each other will produce scatterplots that are oval shaped or elliptical." (p. 69). Hair et al. (2010b) recommended the addition of a regression line to help identify non-linear characteristics. Lines that slope from bottom left to top right depict a positive linear relationship, lines that slope up top left to bottom right depict a negative linear relationship, while lines that are virtually horizontal depict no linear relationship. Appendix M contains bivariate scatterplots for all of the relationships of interest in this study. For each scatterplot, a shape encompassing a majority of the individual data points as well as a regression line have been overlaid. As additional tests for linearity, regression analyses with a focus on an examination of the residuals was completed, as per both Meyers et al. (2006) and Hair et al. (2010b). For each relationship of interest, a histogram and normal P-P plot of the standardized regression residuals, along with a scatterplot of the regression standardized residuals versus the regression standardized predicted values (as per Verran and Ferketich (1987) and Hocking

(2003)) have been included in Appendix M. In this residual analysis, linearity is assumed if the residuals exhibit normality, with the same criteria for normality being applied to the residuals as was applied to the construct/indicators as described above (i.e., histogram of residuals appears indicates normality; normal P-P plot of standardized residuals contains data points that follow the normal distribution diagonal line; for scatterplot of regression standardized residuals versus the regression standardized predicted values "cases distribute themselves evenly above and below the horizontal line that intersects the Y axis at 0.0, the line of zero deviation from expected normal values" (Tabachnick & Fidell, 2006, p. 81)).

In addition to graphical analyses for linearity, SPSS statistical tests of linearity were completed, and are included in Table 12. In this test, if the significance value for linearity has a value smaller than 0.05 it indicates that there is a linear relationship (IBM SPSS Statistics, 2013). The results of this analysis indicate the presence of linearity for all relationships of interest.

Table 12 – Data Linearity Tests

Relationship	Linearity Significance Value	Linear Relationship?
SEV → PTTF	0.000	✓
SEV → SE	0.000	✓
SEV → RE	0.000	✓
VUL → PTTF	0.000	✓
VUL → SE	0.000	✓
VUL → RE	0.000	✓
PAM → PTTF	0.020	✓
PAM → SE	0.002	✓
PTTF → ADOPT	0.000	✓
SE → ADOPT	0.000	✓
RE → ADOPT	0.000	✓
RC → ADOPT	0.003	✓

As both the graphical and statistical analyses indicate, all of the relationships appear to exhibit sufficient linearity. In summary, based on the linearity multivariate statistical assumption, the data set was deemed suitable for further analysis.

Homoscedasticity

The final test for multivariate statistical assumptions involves homoscedasticity. For this current research, a graphical analysis of homoscedasticity was completed. As per Salkind (2010) residual scatterplots "are a useful and basic graphical method to determine homoscedasticity violations" (p. 581). Residual scatterplots plot residual Y values along the Y-axis and predicted or observed Y values along the X-axis. The plot is then analyzed to see if there is a constant spread in the residuals across the values shown along the X-axis (Salkind, 2010). An example of this scatterplot is shown in Figure 10. To aid interpretation, linear fit lines that trace the overall trend of the data at the mean are added to the plot. A flat fit line that intersects the Y-axis at zero provides strong indications of homoscedasticity. Residual scatterplots for all variables in the model have been included in Appendix N, and provide sufficient evidence of the presence of homoscedasticity (IBM SPSS Statistics, 2013) and no violations of the homoscedasticity multivariate statistical assumption. In summary, based on the homoscedasticity multivariate statistical assumption, the data set was deemed suitable for further analysis.

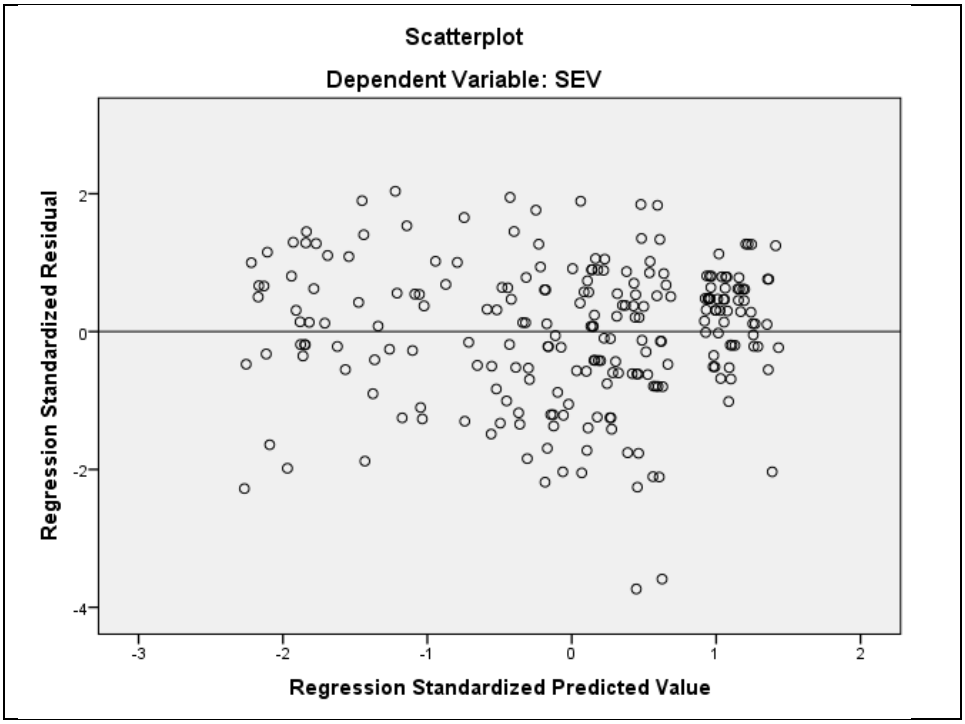


Figure 10 – Residual Scatterplot Homoscedasticity Analysis

6.3 Demographics

Along with the items for the model constructs, a number of general demographic, Type 2 Diabetes information and general health questions were collected from respondents (see Appendix D for a list of these questions). General demographic variables captured were age, gender, marital status, education, income and employment. A full breakdown of the study demographics is provided in Table 13. During the data collection process, quotas were put in place to attempt to match the population breakdown for age and gender of the population with Type 2 Diabetes (see last column in Table 13). In addition to the demographic variables captured during the survey process, country of origin for participants recruited directly by the researcher (i.e., through TuDiabetes support group) was identified by some respondents who provided a physical mailing address for compensation purposes. All respondents recruited through Research Now were from Canada. Based on this information, it can be ascertained that approximately 88.2% of respondents were from Canada, 11.3% of respondents were from the United States and 0.5% of respondents were from an international location.

Table 13 – Survey Participant Demographics

Variable	Count	%	Type 2 Diabetes General Population %
Gender			
Male	122	53.04%	53.73%
Female	108	46.96%	46.27%
TOTAL	**230**	**100%**	**100%**
Age			
18-29	9	3.91%	3.95%
30-39	17	7.39%	6.84%
40-49	43	18.70%	16.10%
50-59	56	24.35%	25.10%
60-69	54	23.48%	23.86%
70+	51	22.17%	24.16%
TOTAL	**230**	**100%**	**100%**
Marital Status			
Single, never legally married	25	10.87%	
Legally married (and not separated)	127	55.22%	
Separated, but still legally married	10	4.35%	
Living with a partner	29	12.61%	
Divorced	21	9.13%	
Widowed	15	6.52%	
No Answer	3	1.30%	
TOTAL	**230**	**100%**	
Education			
Did not complete high school	9	3.91%	
High School	41	17.83%	
Some College or University	44	19.13%	
College or University Degree/Diploma	117	50.87%	
Graduate Degree (Masters or PhD)	16	6.96%	
No Answer	3	1.30%	
TOTAL	**230**	**100%**	
Income			
< $10,000	7	3.04%	
$10,000 - $24,999	29	12.61%	
$25,000 - $49,999	55	23.91%	
$50,000 - $74,999	60	26.09%	
$75,000 - $99,999	39	16.96%	
> $100,000	13	5.65%	
No Answer	27	11.74%	
TOTAL	**230**	**100%**	
Employment			
Employed full-time (35+ hours/week)	77	33.48%	
Employed part-time/casual (less than 35 hours/week)	20	8.70%	
Self-employed	13	5.65%	
Home maker	9	3.91%	
Student (full-time or part-time)	2	0.87%	
Retired	98	42.61%	
Not currently employed	9	3.91%	
No Answer	2	0.87%	
TOTAL	**230**	**100%**	

In addition to capturing basic demographic information, specific Type 2 Diabetes information items for each respondent were captured as potential control variables. Respondents were asked about their perception of their Type 2 Diabetes severity, their level of control over the disease, their knowledge about the disease, as well as how long it has been since they were diagnosed with the disease. Their responses are summarized in Table 14.

Table 14 – Survey Participant Type 2 Diabetes Statistics

Variable	Count	%
Type 2 Diabetes Severity		
Mild	54	23.48%
Mild to Moderate	59	25.65%
Moderate	81	35.22%
Moderate to Severe	33	14.35%
Severe	2	0.87%
No Answer	1	0.43%
TOTAL	**230**	**100%**
Type 2 Diabetes Knowledge		
Poor	5	2.17%
Fair	53	23.04%
Good	116	50.43%
Very Good	52	22.61%
Excellent	3	1.30%
No Answer	1	0.43%
TOTAL	**230**	**100%**
Type 2 Diabetes Control		
Very Poorly Controlled	1	0.43%
Poorly Controlled	17	7.39%
Moderately Controlled	114	49.57%
Well Controlled	80	34.78%
Very Well Controlled	17	7.39%
No Answer	1	0.43%
TOTAL	**230**	**100%**
Type 2 Diabetes Time Since Diagnosis		
<1 Year	2	0.87%
1-4 Years	49	21.30%
5-9 Years	83	36.09%
10-19 Years	72	31.30%
20-29 Years	16	6.96%
30+ Years	5	2.17%
No Answer	3	1.30%
TOTAL	**230**	**100%**

Finally, participants were asked two questions about general health, including their perception of their current health status as well as their general health knowledge. A summary of their responses is included in Table 15.

Table 15 – Survey Participant General Health Statistics

Variable	Count	%
General Health Condition		
Poor	11	4.78%
Fair	60	26.09%
Good	118	51.30%
Very Good	33	14.35%
Excellent	3	1.30%
No Answer	5	2.17%
TOTAL	**230**	**100%**
General Health Knowledge		
Poor	2	0.87%
Fair	35	15.22%
Good	121	52.61%
Very Good	58	25.22%
Excellent	9	3.91%
No Answer	5	2.17%
TOTAL	**230**	**100%**

6.4 Research Model Assessment

The research model was assessed both for the measurement model as well as the structural model. Additionally, an examination of common method bias was completed. Given the research model contains a single formative construct, the model is therefore considered to be a formative one (Petter, et al., 2007), as detailed in Chapter 5. The statistical techniques to evaluate construct validity and reliability differ for formative versus reflective constructs. Therefore, the methods used to evaluate these different types of constructs differ, as do the methods of structural model evaluation (Petter, et al., 2007).

6.4.1 Measurement Model

Reflective Constructs

For reflective construct evaluation, the procedures for evaluating the constructs when using the PLS approach as per Götz et al. (2010) were followed. Specifically, content validity, indicator reliability, construct reliability and convergent/discriminant validity were assessed. As a first step, convergent and discriminant validity was tested to determine if any indicators needed to be removed due to potential loading or cross-loading issues. Indicators should be examined to ensure they load on their theoretically assigned latent construct more highly than they load on any other latent construct (Gefen & Straub, 2005).

As Table 16 indicates, all indicators did load most highly on their own theoretically assigned construct, and at a minimum threshold of 0.70, as per Fornell and Larcker (1981). It should be noted that the PAM construct was not included in this analysis, as it is a single-item measure and therefore results in a loading of 1.000. No cross-loading issues were identified between the PAM construct and any other construct.

Gefen and Straub (2005) recommend that "loadings of the measurement items on their assigned latent variables should be an order of magnitude larger than any other loading" (p. 93), providing specifically that this difference should be at least 0.10. Therefore, this analysis took an iterative approach in examining the cross-loadings, examining the differences between the indicator loading and the next highest loading, to ensure that this difference was the minimum 0.10 difference. In each iteration, the indicator with the smallest difference (which was less than 0.10) in these two values was removed, and the analysis was run again. This process continued until the minimum difference in the values were all greater than 0.10, and revealed that some PTTF indicators should be removed. The final set of indicators used for the remainder of the analysis, all with loadings of at least 0.10 higher on their assigned theoretical construct than any other construct, are provided in Table 17. The remainder of the reflective measurement analysis and the structural analysis therefore uses these indicators.

Table 16 – Initial Indictor Loadings and Cross-Loadings

	ADOPT	PTTF	RE	SE	SEV	VUL
ADOPT1	**0.947**	0.762	0.745	0.607	0.345	0.356
ADOPT2	**0.960**	0.775	0.761	0.633	0.346	0.381
ADOPT3	**0.962**	0.792	0.774	0.642	0.360	0.416
PTTF1	0.619	**0.808**	0.682	0.589	0.389	0.357
PTTF2	0.705	**0.851**	0.775	0.621	0.352	0.334
PTTF3	0.711	**0.869**	0.779	0.579	0.366	0.428
PTTF4	0.665	**0.828**	0.717	0.576	0.373	0.390
PTTF5	0.690	**0.854**	0.766	0.567	0.334	0.360
PTTF6	0.552	**0.755**	0.626	0.572	0.369	0.374
PTTF7	0.698	**0.835**	0.786	0.579	0.369	0.337
PTTF8	0.739	**0.843**	0.772	0.589	0.340	0.371
RE1	0.663	0.751	**0.868**	0.632	0.377	0.379
RE2	0.715	0.791	**0.882**	0.594	0.402	0.391
RE3	0.646	0.765	**0.864**	0.596	0.375	0.361
RE4	0.769	0.828	**0.911**	0.622	0.396	0.418
SE1	0.560	0.548	0.539	**0.751**	0.189	0.239
SE2	0.600	0.627	0.618	**0.771**	0.271	0.382
SE3	0.314	0.407	0.386	**0.718**	0.252	0.298
SE4	0.413	0.465	0.475	**0.737**	0.235	0.278
SEV1	0.310	0.392	0.393	0.245	**0.717**	0.537
SEV2	0.257	0.292	0.323	0.230	**0.755**	0.536
SEV3	0.293	0.296	0.299	0.244	**0.832**	0.624
SEV4	0.337	0.359	0.362	0.278	**0.849**	0.674
SEV5	0.226	0.324	0.314	0.232	**0.713**	0.550
SEV6	0.266	0.334	0.336	0.230	**0.777**	0.608
VUL1	0.385	0.432	0.436	0.347	0.719	**0.911**
VUL2	0.343	0.384	0.365	0.346	0.649	**0.890**
VUL3	0.361	0.389	0.406	0.378	0.671	**0.876**
VUL4	0.346	0.378	0.362	0.371	0.678	**0.896**

Table 17 – Final Reflective Indicator Loadings and Cross-Loadings

	ADOPT	PTTF	RE	SE	SEV	VUL	DIFFERENCE (Largest – 2nd)
ADOPT1	**0.947**	0.673	0.745	0.607	0.346	0.356	**0.202**
ADOPT2	**0.960**	0.671	0.761	0.633	0.346	0.381	**0.199**
ADOPT3	**0.962**	0.699	0.774	0.642	0.360	0.416	**0.188**
PTTF1	0.619	**0.898**	0.682	0.589	0.389	0.357	**0.216**
PTTF4	0.665	**0.865**	0.717	0.576	0.372	0.390	**0.148**
PTTF6	0.552	**0.822**	0.626	0.572	0.369	0.374	**0.196**
RE1	0.663	0.665	**0.868**	0.632	0.377	0.379	**0.203**
RE2	0.715	0.693	**0.882**	0.594	0.401	0.391	**0.167**
RE3	0.646	0.659	**0.864**	0.596	0.374	0.360	**0.205**
RE4	0.769	0.743	**0.911**	0.622	0.396	0.418	**0.142**
SE1	0.560	0.525	0.539	**0.751**	0.190	0.239	**0.190**
SE2	0.600	0.539	0.618	**0.771**	0.270	0.382	**0.153**
SE3	0.314	0.422	0.386	**0.718**	0.252	0.299	**0.296**
SE4	0.413	0.493	0.475	**0.737**	0.235	0.279	**0.244**
SEV1	0.310	0.389	0.393	0.245	**0.715**	0.537	**0.178**
SEV2	0.257	0.302	0.323	0.230	**0.759**	0.537	**0.222**
SEV3	0.293	0.312	0.299	0.244	**0.834**	0.624	**0.210**
SEV4	0.337	0.370	0.362	0.278	**0.851**	0.674	**0.177**
SEV5	0.226	0.326	0.314	0.232	**0.710**	0.550	**0.160**
SEV6	0.266	0.312	0.336	0.230	**0.773**	0.608	**0.165**
VUL1	0.385	0.410	0.436	0.347	0.719	**0.910**	**0.191**
VUL2	0.343	0.354	0.365	0.346	0.648	**0.889**	**0.240**
VUL3	0.361	0.384	0.406	0.378	0.672	**0.877**	**0.205**
VUL4	0.346	0.399	0.362	0.371	0.678	**0.899**	**0.221**

Content validity essentially involves the issue of representation, specifically the degree to which the construct indicators measure their given construct (Straub, et al., 2004). The literature notes that content validity is not easy to assess, but is best done through literature reviews and expert judges and panels, and that empirical assessment of this type of validity is typically not required (Straub, et al., 2004). This study addresses the issue of content validity through the use of previously validated scales for all of the non-PMT constructs (i.e., ADOPT, PTTF, PAM) and one of the PMT constructs (i.e., SE). The lone PMT construct that only made use of a previously validated scale was SE, as the SE construct in this model is technology self-efficacy, and therefore an adapted version of the computer self-efficacy scale was used (as detailed in Section 5.4). For the remaining PMT constructs, an additional step was taken,

with the use of previously validated scales from relevant PMT studies that were then adapted based on a focus group session that was conducted with people who have Type 2 Diabetes to ensure the most salient measures for RE, SEV, VUL and RC were captured. These scales were then tested in the pilot study and revised where necessary for the final main study. This method of developing scales for PMT studies is recommended by experts in the area of PMT. Norman et al. (2005) indicated that two methods could be used to develop of a PMT questionnaire. The first method was to conduct a literature review of previous PMT studies. This current study examined a large number of prior previous PMT studies, focusing on those that were highly cited (Norman, et al., 2003) as well as those that specifically focused on Diabetes (Plotnikoff, et al., 2010; Plotnikoff, et al., 2009b; Plotnikoff, et al., 2008). In addition, Norman et al. (2005) recommend the use of interviews with people drawn from the target population. This current study used a focus group session conducted with people who currently have Type 2 Diabetes to refine the items that were created from prior literature. Given this current study utilized previously validated scales and/or applied both of the methods outlined by Norman et al. (2005), this demonstrates the necessary requirements of content validity.

Indicator reliability "specifies which part of an indicator's variance can be explained by the underlying latent variable" (Götz, et al., 2010, p. 694). To assess indicator reliability, indicator loadings are examined to determine if they are above the 0.70 threshold (Fornell & Larcker, 1981). For this study, all indicators loaded at the 0.70 threshold or better, with 16 of 24 (or 66.7%) indicators loading above 0.80, as shown in Table 18. In all cases the indicator loadings were significant at the $p < 0.001$ level. Therefore, from this criterion, indicator reliability requirements are met. In addition, in the process described earlier, a cross-loading analysis served to include items whereby the indicator loadings were all of an order of magnitude (i.e., 0.10) higher on their own theoretically assigned construct than on any other construct, further indicting evidence of indicator reliability (see Table 17).

Table 18 – Indicator Descriptive Statistics, Loadings and Significance

	n	Mean	Std. Deviation	Loading	T-Statistic	Significance
ADOPT1	230	5.32	1.237	0.947	65.773	p < 0.001
ADOPT2	230	5.29	1.277	0.960	128.806	p < 0.001
ADOPT3	230	5.28	1.275	0.962	149.318	p < 0.001
PTTF1	230	5.33	0.959	0.898	57.918	p < 0.001
PTTF4	230	5.38	0.921	0.865	38.169	p < 0.001
PTTF6	230	5.13	1.220	0.822	27.977	p < 0.001
RE1	230	5.53	.988	0.868	42.056	p < 0.001
RE2	230	5.38	1.074	0.882	49.848	p < 0.001
RE3	230	5.31	1.124	0.864	40.079	p < 0.001
RE4	230	5.53	1.052	0.911	75.509	p < 0.001
SE1	230	5.33	1.209	0.751	20.655	p < 0.001
SE2	230	5.35	1.187	0.771	24.322	p < 0.001
SE3	230	5.07	1.229	0.718	11.842	p < 0.001
SE4	230	4.93	1.328	0.737	15.169	p < 0.001
SEV1	230	5.67	1.104	0.715	16.072	p < 0.001
SEV2	230	4.42	1.552	0.759	19.649	p < 0.001
SEV3	230	4.45	1.517	0.834	30.350	p < 0.001
SEV4	230	4.73	1.456	0.851	36.451	p < 0.001
SEV5	230	5.59	1.097	0.710	15.979	p < 0.001
SEV6	230	5.58	1.082	0.773	20.124	p < 0.001
VUL1	230	5.60	1.108	0.910	61.672	p < 0.001
VUL2	230	5.50	1.218	0.889	48.768	p < 0.001
VUL3	230	4.95	1.396	0.877	48.013	p < 0.001
VUL4	230	5.43	1.153	0.899	56.710	p < 0.001

Construct reliability shows that "all the construct's indicators jointly measure the construct adequately" (Götz, et al., 2010, p. 695). Construct reliability can be assessed via Composite Reliability measures. Fornell and Larcker (1981) indicate that construct reliability is evidenced by Composite Reliability measures that are greater than 0.80. As Table 19 indicates, all Composite Reliability values were greater than the 0.80 threshold. In fact, four of the six construct (i.e., ADOPT, RE, SEV and VUL) values were greater than or equal to 0.90, with one other construct (i.e., PTTF) value at 0.897. The lowest Composite Reliability was 0.833 for the SE construct. In addition, internal consistency Cronbach's Alpha (α) statistics are included in Table 19. As per Hair et al. (2010b), Cronbach's Alpha statistics between 0.60 and 0.70 are deemed to be at the low end of acceptability. Therefore values should exceed a 0.70

threshold (a value recommended originally by Cronbach (1951)). As Table 19 demonstrates, all Cronbach's Alpha (α) values exceed the 0.70 threshold, with three constructs (ADOPT, RE and VUL) exceeding 0.90 and another two constructs (PTTF and SEV) exceeding 0.80, with SE having the lowest value at 0.737. Therefore, based on these criteria, construct reliability requirements are met.

Table 19 – Reflective Construct Reliability and Validity Statistics

	AVE	$\sqrt{AVE}$	Composite Reliability	Cronbach's Alpha	Communality
ADOPT	0.915	0.957	0.970	0.954	0.915
PTTF	0.743	0.862	0.897	0.827	0.743
RE	0.777	0.881	0.933	0.904	0.777
SE	0.554	0.745	0.833	0.737	0.554
SEV	0.602	0.776	0.900	0.866	0.602
VUL	0.798	0.894	0.941	0.916	0.798

Straub et al. (2004) define construct validity as "an issue of operationalization or measurement between constructs" and "the basic question of whether the measures chosen by the researcher 'fit' together in such as way so as to capture the essence of the construct" (p. 388). For construct validity, both convergent as well as discriminant validity were examined. Convergent validity "is based on the correlation between responses obtained by maximally different methods of measuring the same construct" (Götz, et al., 2010, p. 696). To assess convergent validity, Average Variance Extracted (AVE) values should exceed the 0.50 threshold (Fornell & Larcker, 1981; Götz, et al., 2010). As Table 19 shows, all AVEs are above the 0.5 threshold (and the square root of the AVE is above the 0.707 threshold), thus providing evidence of sufficient convergent validity. Discriminant validity is defined as "the dissimilarity in a measurement tool's measurement of different constructs" (Götz, et al., 2010, p. 696). To assess discriminant validity, an examination of the AVE versus the squared correlations is made, or more commonly, an examination of the square root of the AVE versus the correlations of the latent variables is made. Discriminant validity is proven when the square root of the AVE for a latent construct is larger than the correlations the construct has with any other construct (Fornell & Larcker, 1981). As demonstrated in Table 20, all square roots of the AVEs for each construct are greater than the correlation with any other construct, thus providing evidence of discriminant validity.

Table 20 – Construct Correlations and Square Roots of the AVEs

	ADOPT	PAM	PTTF	RE	SE	SEV	VUL
ADOPT	**0.957**						
PAM	0.126	**1.000**					
PTTF	0.712	0.148	**0.862**				
RE	0.795	0.068	0.785	**0.881**			
SE	0.656	0.192	0.672	0.693	**0.745**		
SEV	0.367	-0.103	0.437	0.440	0.316	**0.776**	
VUL	0.402	-0.073	0.433	0.440	0.404	0.761	**0.894**

** Bolded values on the diagonal are square roots of the AVEs*
RC has not been included as it is a formative construct

In summary, the above reflective construct analysis indicates that the measurement model meets all the required criteria to proceed to the next step, namely structural model analysis. However, before moving on to that step, a formative construct analysis, multicollinearity analysis as well as a Common Method Bias (CMB) analysis are required.

Formative Constructs

To accurately assess the formative construct in the model, the methods outlined by Petter et al. (2007) are used. As a first step, it is important to ensure that constructs are correctly identified as formative, rather than simply stating this supposition. Petter et al. (2007) recommend a four step process, as follows:

Step 1: "consider the theoretical direction of causality between each construct and its measures. If the direction of causality is from the construct to the items, the construct is reflective. If causality is directed from the items to the construct, the construct is formative."

Step 2: "examine the inter-changeability of the measures. Measures that are inter-changeable and have a common theme are typically reflective. Good reflective measures, by definition, should be unidimensional and reflect this common theme. Formative measures may not be interchangeable and will often employ different themes. Furthermore, with formative measures, dropping one of the measures would affect the meaning of the construct since the construct is defined by these measures."

Step 3: "With formative constructs, though, measures do not need to covary. In fact, formative measures should not have strong correlations with one another because this suggests multicollinearity."

Step 4: "final decision rule to identify formative constructs asks if the measures of the construct have the same antecedents and consequences. Formative constructs are composites or indices that are made up of measures that may be very different; thus, it is not necessary for the measures to have the same antecedents and consequences."

Note, above 4 steps were all taken from Petter et al. (2007, pp. 633-634)

Prior to data collection, the construct of Response Costs in the model was identified as formative, however it must be verified that it meets all of the criteria defined by Petter et al. (2007). The four indicators that were used for the formative Response Costs construct are:

1. I would be discouraged from using an ePHR because it would take too much time.
2. I am concerned about the privacy and security of my health information if I use an ePHR.
3. I am concerned that it would be expensive to use an ePHR.
4. I feel the potential costs of using an ePHR would outweigh the benefits.

Table 21 summarizes the analysis of the Response Cost construct through an assessment of the four steps outlined by Petter et al. (2007).

Table 21 – Formative Construct Assessment

Step	Rule	Response Cost Construct Assessment
1	Direction of causality	The indicators define the characteristics of the construct and are not manifestations of the construct. Therefore, this construct exhibits characteristics of being formative.
2	Inter-changeability of measures	Indicators are not interchangeable, do not have similar content, do not share a common theme and dropping any one of the items would alter the nature of the construct. Therefore, this construct exhibits characteristics of being formative.
3	Covariance/Correlation	Correlations indicate items may covary with one another (See Table 23). However, according to Petter et al. (2007) the items may covary, but do not necessarily need to covary, as they do with reflective construct items. Further analysis reveals multicollinearity not deemed to be an issue due to all VIF values less than 3.3 (see Table 24). Therefore, this construct exhibits characteristics of being formative.
4	Antecedents and consequences	Items do not have the same antecedents and/or consequences. For example, the antecedents of question 1 are time related, antecedents of question 2 are security and privacy related while the antecedents for question 3 are monetary related. Similarly, the consequences of question 1 could be effort, while the consequences of question 2 could be trust. Therefore, this construct exhibits characteristics of being formative.

Based on the above assessment, the Response Cost construct is deemed to be formative. This construct was therefore assessed using the methods outlined by Petter et al. (2007) for both construct validity and reliability. First, to assess construct validity, the weights (not the loadings) were analyzed. Lohmöller (1989) recommends that the weight (or the path coefficient from the indicator to the formative construct) should be greater than 0.1, a criteria that is met by three of the four indicators for the formative Response Cost construct (see Table 22). However, Table 22 indicates that only one of the four item weights is significant, thus indicating potential validity issues. When indicators are nonsignificant, the researcher must decide whether to keep or remove the nonsignificant item(s). The researcher may remove the items, as per Diamantopoulos and Winklhofer (2001). Alternatively, as per Bollen and Lennox (1991) (cited in Petter et al. (2007)), a researcher "may choose to keep nonsignificant items to preserve content validity" (p. 642). Given that the nonsignificant items are important to content validity (these items dealt with monetary cost, security/privacy of the ePHR and overall cost benefit), the decision to keep the nonsignificant items was made.

Table 22 – Formative Construct Descriptives, Weights and Significance

	n	Mean	Std. Deviation	Weight	Significance
RC1	230	3.87	1.620	0.683	13.740***
RC2	230	3.93	1.613	-0.119	1.345
RC3	230	4.59	1.370	-0.138	1.223
RC4	230	4.17	1.490	-0.023	0.296

**** significant at p<0.001*

As a next step, an assessment of construct reliability through indicator collinearity was completed. Table 23 provides an inter-item correlation matrix, and shows that all values are below the 0.8 threshold as suggested by Stevens (2012). Next, an examination of potential multicollinearity issues as per Petter et al. (2007) through the analysis of Variance Inflation Factors (VIFs) was completed, as detailed in Table 24. For formative construct analysis, Tolerance values less than 0.01 or VIFs that are greater than 3.3 may indicate potential multicollinearity issues (Petter, et al., 2007). An iterative process whereby regression analyses were run with each individual indicator (as the dependent) with all other indicators (as the independents), as well as a composite of all RC indicators (as the dependent) with all individual indicators (as the independents) was completed. Given all of the Tolerance values are much larger than 0.01 and the highest VIF value revealed through this process was 2.320, this analysis showed no multicollinearity issues for the formative Response Cost construct, and therefore this formative construct meets the required reliability criteria.

Table 23 – Response Cost Inter-Item Correlation Matrix

	RC1	RC2	RC3	RC4
RC1	1.000			
RC2	.460	1.000		
RC3	.280	.545	1.000	
RC4	.455	.468	.702	1.000

Table 24 – Formative Construct Variance Inflation Factor (VIF) Analysis

Dependent	Independent	Tolerance	VIF	Multicollinearity?
RC1	RC2	.689	1.452	NO
	RC3	.447	2.236	NO
	RC4	.497	2.012	NO
RC2	RC1	.505	1.979	NO
	RC3	.435	2.299	NO
	RC4	.790	1.265	NO
RC3	RC1	.715	1.398	NO
	RC2	.704	1.420	NO
	RC4	.708	1.412	NO
RC4	RC1	.788	1.270	NO
	RC2	.601	1.665	NO
	RC3	.702	1.425	NO
RC (Composite)	RC1	.689	1.451	NO
	RC2	.601	1.665	NO
	RC3	.431	2.320	NO
	RC4	.435	2.299	NO

As a final step, an examination of external validity of the formative construct was completed as per Diamantopoulos and Winklhofer (2001). A two construct Multiple Indicators, Multiple Constructs (MIMIC) model with formative and reflective indicators was constructed and tested in AMOS Version 21 (see Figure 11). A covariance based approach to developing the MIMIC model was used (i.e., AMOS), as PLS models do not produce the necessary fit indices required for this analysis. The results of this analysis indicated a large path coefficient (i.e., -0.320) between the formative Response Costs construct and PHR Adoption Intention, which is significant at the $p<0.001$ level. In addition, the two construct MIMIC model showed good fit with $X^2 = 4.864$, df = 9; $X^2/df = 0.54$; p = 0.846; RMSEA = 0.000; RMSR = 0.029; PCLOSE = 0.969; CFI = 1.00; GFI = 0.994; and AGFI = 0.981. As per Diamantopoulos and Winklhofer (2001) "If the overall model fit proves acceptable, this can be taken as supporting evidence for the set of indicators forming the index" (p. 272).

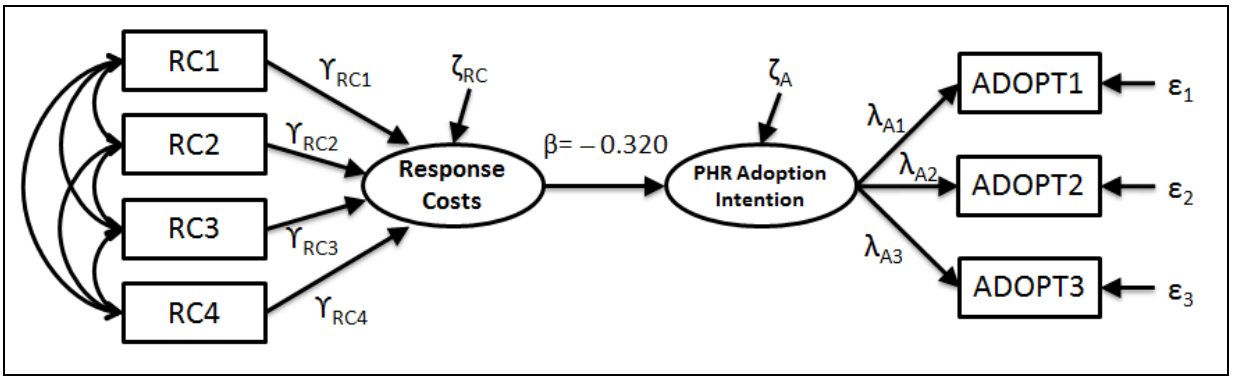


Figure 11 – Two Construct MIMIC Model

In summary, this formative construct analysis shows that the Response Cost construct meets all of the criteria to be considered a formative construct, and that it meets the required reliability and validity requirements. Therefore, this formative construct was used in the subsequent structural model analysis.

Multicollinearity

Multicollinearity is defined as the "Extent to which a variable can be explained through the other variables in the analysis. As multicollinearity increases, it complicates the interpretation of the variate, because it is more difficult to ascertain the effect of any single variable, owing to their interrelationships." (Hair, et al., 2010b, p. 2). In order to assess multicollinearity, an examination of the inter-construct correlations was made. Bivariate correlations greater than 0.80 may indicate the potential need to remove a variable due to multicollinearity (Meyers, et al., 2006) or to combine variables into a larger construct (Stevens, 2012). As the output from SPSS in Table 25 shows, none of the inter-construct correlations are indicative of any issues with multicollinearity.

Table 25 – Inter-Construct Bivariate Correlations

	SEV	VUL	ADOPT	RE	PTTF	SE	PAM	RC
SEV	**1.000**							
VUL	0.753	**1.000**						
ADOPT	0.361	0.401	**1.000**					
RE	0.428	0.438	0.792	**1.000**				
PTTF	0.427	0.433	0.704	0.777	**1.000**			
SE	0.313	0.400	0.627	0.672	0.662	**1.000**		
PAM	-0.105	-0.072	0.126	0.065	0.154	0.198	**1.000**	
RC	0.015	0.002	-0.193	-0.252	-0.178	-0.168	-0.178	**1.000**

** Note that correlations may differ slightly from Table 20, as different statistical software programs were used*

A more advanced analysis of multicollinearity can be completed by examining the Tolerance and Variance Inflation Factor (VIF) statistics produced by SPSS. As per Meyers et al. (2006), multicollinearity is a condition that exists when predictor variables are strongly correlated and not applicable to correlations between predictor variables and the dependent variables. Therefore, the Tolerance and VIF analysis was completed between predictor variables. Through an iterative process, regression analyses were completed, with each predictor variable in the model set as the dependent and all of the remaining predictor variables set as the independents. The results of this analysis are shown in Table 26. Tolerance values less than 0.01 may indicate multicollinearity, and all of the Tolerance values for this study are well above this threshold. All of the VIFs are below the commonly cited cut-off thresholds of 10 (Stevens, 2012; Vinzi, et al., 2010a), 5 (Berk, 2003; Hair, et al., 2011), 4 (O'Brien, 2007) and 3.3 (Petter, et al., 2007). Therefore, multicollinearity is not deemed to be an issue for this research study.

Table 26 – Construct Multicollinearity Analysis

Dependent		Independent						
		SEV	**VUL**	**PAM**	**PTTF**	**SE**	**RE**	**RC**
SEV	Tolerance		.747	.893	.348	.475	.327	.898
	VIF		1.339	1.120	2.871	2.105	3.062	1.114
VUL	Tolerance	.759		.889	.343	.485	.324	.896
	VIF	1.318		1.125	2.911	2.062	3.089	1.116
PAM	Tolerance	.409	.401		.350	.484	.330	.916
	VIF	2.444	2.494		2.854	2.065	3.034	1.092
PTTF	Tolerance	.412	.400	.905		.503	.468	.896
	VIF	2.426	2.500	1.105		1.988	2.137	1.117
SE	Tolerance	.411	.413	.915	.368		.362	.895
	VIF	2.430	2.420	1.093	2.716		2.759	1.117
RE	Tolerance	.410	.400	.904	.497	.526		.936
	VIF	2.437	2.499	1.107	2.013	1.902		1.068
RC	Tolerance	.408	.400	.908	.344	.469	.338	
	VIF	2.453	2.498	1.102	2.910	2.131	2.956	

6.4.2 Common Method Bias

When data is collected through survey self-reports, it is important to examine the potential effects that common method bias (also known as common method variance) may have on the research. Common method variance "can cause researchers to find a significant effect, when in fact, the true effect is due to the method employed" (Woszczynski & Whitman, 2004, p. 66). It is recommended that researchers examine and model method effects (Woszczynski & Whitman, 2004) and therefore this research study examines common method bias in two different ways. First, the traditional and well recognized Harman's One-Factor Test was employed. In this test, an exploratory factor analysis is completed to examine the number of factors that account for the variance. If common method variance is present, "either (a) a single factor will emerge from the factor analysis or (b) one general factor will account for the majority of the covariance among the measures" (Podsakoff, et al., 2003, p. 889). SPSS was used to conduct a Principal Component Analysis with no rotation, and an extraction based on Eigenvalues greater

than 1. All of the multi-item variables of interest (note, PAM was not included, as it is a single-item measure) were entered into this analysis. The results are included in Table 27. The results show that a multi-factor solution emerged, with the first factor accounting for only 38.514% of the variance, and the first 5 factors accounting for 69.351% of the variance.

Table 27 – Principal Component Analysis Without Rotation

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.784	**38.514**	38.514	10.784	**38.514**	38.514
2	3.846	13.737	52.251	3.846	13.737	52.251
3	2.288	8.171	60.422	2.288	8.171	60.422
4	1.323	4.725	65.147	1.323	4.725	65.147
5	1.177	4.204	69.351	1.177	4.204	69.351
6	.925	3.302	72.653			
⋮						
28	.084	.301	100.000			

The same analysis was run using a Varimax Rotation in Principal Component Analysis in SPSS (see Table 28). In this rotated solution, the first factor only accounts for only 27.936% of the variance. The results of these two analyses (both un-rotated and rotated) provide sufficient evidence that the variables in the model do not load onto one factor, and that the possibility of common method variance is low.

Table 28 – Principal Component Analysis With Rotation

	Initial Eigenvalues			Rotation Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.784	**38.514**	38.514	7.822	**27.936**	27.936
2	3.846	13.737	52.251	4.853	17.334	45.270
3	2.288	8.171	60.422	2.505	8.945	54.214
4	1.323	4.725	65.147	2.497	8.917	63.132
5	1.177	4.204	69.351	1.741	6.219	69.351
6	.925	3.302	72.653			
⋮						
28	.084	.301	100.000			

While the Harman's One-Factor Test is very often used to identify the presence of common method variance, Podsakoff et al. (2003) noted that the test suffers from a number of limitations. Most notably, it

is not likely that a one-factor solution will emerge and therefore it is recommended that other statistical methods should be used (Podsakoff, et al., 2003). Over the years, a number of other methods to detect common method bias have been proposed and used, in most cases with noted limitations (Chin, et al., 2012). One method that has witnessed significant usage since its introduction is the Liang et al. (2007) method of using PLS to assess common method bias (found in Appendix E of the Liang paper). This paper has been cited over 600 times according to Google Scholar, with at least 76 of these citations referencing the approach used for assessing common method bias (Chin, et al., 2012). In this method, categorized by Chin et al. (2012) as an Unmeasured Latent Marker Construct (ULMC) technique, variance of an indicator is partitioned into trait, method and random error. As detailed by Liang et al. (2007), a common latent factor, that is comprised of all indicators in the model is created and added to the structural model. In addition, each indicator was converted into a single-indicator construct (therefore all constructs of interest and the common method factor become second-order constructs). In this new structural model, each indicator construct was then assessed by examining the coefficients of the two paths connected to each indicator construct (i.e., from the substantive construct and from the method construct) to assess the presence of common method bias. These results have been included in Table 29.

As per Liang et al. (2007), "evidence of common method bias can be obtained by examining the statistical significance of factor loadings of the method factor and comparing the variances of each observed indicator explained by its substantive construct and the method factor. The squared values of the method factor loadings [can be] interpreted as the percent of indicator variance caused by method, whereas the squared loadings of substantive constructs [can be] interpreted as the percent of indicator variance caused by substantive constructs. If the method factor loadings are insignificant and the indicators' substantive variances are substantially greater than their method variances, it can be concluded that common method bias is unlikely to be a serious concern." (p. 87). As the results in Table 29 indicate, there are a limited number (i.e., 4) of indicators where the method factor loading was significant. However, all of the substantive factor loadings were found to be significant. In all cases the significance levels of the substantive factor loadings were much larger than the method factor loadings. Finally,

considerably more of the variance for the indicators is caused by the substantive construct (i.e., averaging 0.707) versus the variance caused by the method construct (i.e., averaging 0.012). This ratio of substantive variance to method variance is 59:1, providing sufficient evidence that method variance is not an issue in this study.

As a first step in this process, as per Liang et al. (2007) the model was examined with the Response Costs construct as both a formative construct and a reflective construct to determine if the model assessed in this process could be reflective (i.e., with Response Costs modeled as a reflective construct). As per Liang et al. (2007) if there are no qualitative differences on the statistical results (i.e., no paths change signs, no relationships lose significance), a reflective model can be used. In this data, the path between Response Costs and PHR Adoption Intention did not change signs, and it retained significance (i.e., $t=1.686$, $p < .05$). Finally, one limitation to the Liang et al. (2007) method should be noted. In the recent Chin et al. (2012) paper, the results of the ULMC technique were questioned, specifically whether the technique is able to accurately identify the existence of common method bias. However, at the time of data collection, the Liang et al. (2007) method was one of the most used approaches for this purpose. In addition, in the Chin et al. (2012) study, no alternative solution to assessing common method bias was proposed, and therefore at the time of data analysis, the Liang et al. (2007) method was deemed the most suitable option available. While the Liang et al. (2007) method has been critiqued, the Chin et al. (2012) paper does not necessarily show that the method does not work in all cases, and in fact there may be many cases where the ULMC method does indeed correctly assess CMB. Therefore, this research used the ULMC method in addition to the Harman's One-Factor Test in an effort to be robust in discounting the presence of CMB.

It is also important to note that efforts to reduce the effects of common method bias were taken in the completion of the data collection. First, the proper ordering of questions to control for priming effects (Podsakoff, et al., 2003) was employed. Specifically, wherever possible the endogenous construct responses were gathered prior to the other constructs. For example, the responses for ADOPT were captured before the responses for SE, RE, PTTF and RC. Secondly, respondents were assured of the

anonymity of their responses. Protecting respondent anonymity is one method of controlling common method bias (Podsakoff, et al., 2003).

Overall, based on the procedural remedies employed to reduce common method bias, coupled with the statistical methods used to determine the absence of common method bias, it can be concluded that common method bias is not an issue for this study.

Table 29 – ULMC Common Method Bias Statistics

		Method Factor Loadings			Substantive Factor Loadings			
Construct	**Indicator**	**Loading**	**Significance**	**Loading²**	**Loading**	**Significance**		**Loading²**
ADOPT	**ADOPT1**	-0.037	0.617	0.001	0.979	21.434	***	0.958
	ADOPT2	-0.013	0.319	0.000	0.971	28.227	***	0.943
	ADOPT3	0.049	1.363	0.002	0.921	28.026	***	0.847
PTTF	**PTTF1**	-0.098	1.692	0.010	0.986	21.549	***	0.972
	PTTF4	0.123	1.927	0.015	0.755	13.775	***	0.570
	PTTF6	-0.025	0.307	0.001	0.843	10.882	***	0.711
RC	**RC1**	-0.265	5.292 ***	0.070	0.616	10.185	***	0.380
	RC2	0.046	1.060	0.002	0.795	26.361	***	0.633
	RC3	0.175	4.972 ***	0.031	0.859	31.466	***	0.739
	RC4	0.005	0.137	0.000	0.851	41.002	***	0.725
RE	**RE1**	-0.035	0.500	0.001	0.899	13.818	***	0.808
	RE2	0.040	0.490	0.002	0.844	10.372	***	0.713
	RE3	-0.098	1.272	0.010	0.958	13.216	***	0.917
	RE4	0.086	1.189	0.007	0.830	12.465	***	0.689
SE	**SE1**	0.092	0.944	0.008	0.643	7.041	***	0.414
	SE2	0.263	2.459 *	0.069	0.544	5.308	***	0.295
	SE3	-0.232	3.599 ***	0.054	0.939	19.034	***	0.882
	SE4	-0.132	1.415	0.017	0.871	11.066	***	0.758
SEV	**SEV1**	0.134	1.949	0.018	0.595	7.549	***	0.354
	SEV2	-0.066	1.187	0.004	0.822	16.843	***	0.676
	SEV3	-0.098	1.967	0.010	0.921	27.657	***	0.848
	SEV4	0.006	0.129	0.000	0.854	26.674	***	0.729
	SEV5	0.030	0.456	0.001	0.680	10.904	***	0.462
	SEV6	0.018	0.279	0.000	0.754	13.599	***	0.569
VUL	**VUL1**	0.044	1.149	0.002	0.879	26.163	***	0.773
	VUL2	-0.034	0.936	0.001	0.916	30.159	***	0.839
	VUL3	0.025	0.477	0.001	0.856	19.481	***	0.733
	VUL4	-0.036	0.904	0.001	0.923	28.784	***	0.852
Average		**-0.001**	**1.392**	**0.012**	**0.832**	**19.037**	*******	**0.707**

** = p < .05, *** = p < .001*

6.4.3 Structural Model

Once a satisfactory assessment of the measurement model has been completed, the next step in the analysis process is an examination of the structural model. To examine the structural model and to assess the hypotheses developed, the methods recommended by a number of experts in the area of PLS based analyses were used (Chin, 2010; Hair, et al., 2011; Hair, et al., 2012; Petter, et al., 2007; Roldán & Sánchez-Franco, 2012). The results of the structural model are shown below in Figure 12, and detailed in the following section.

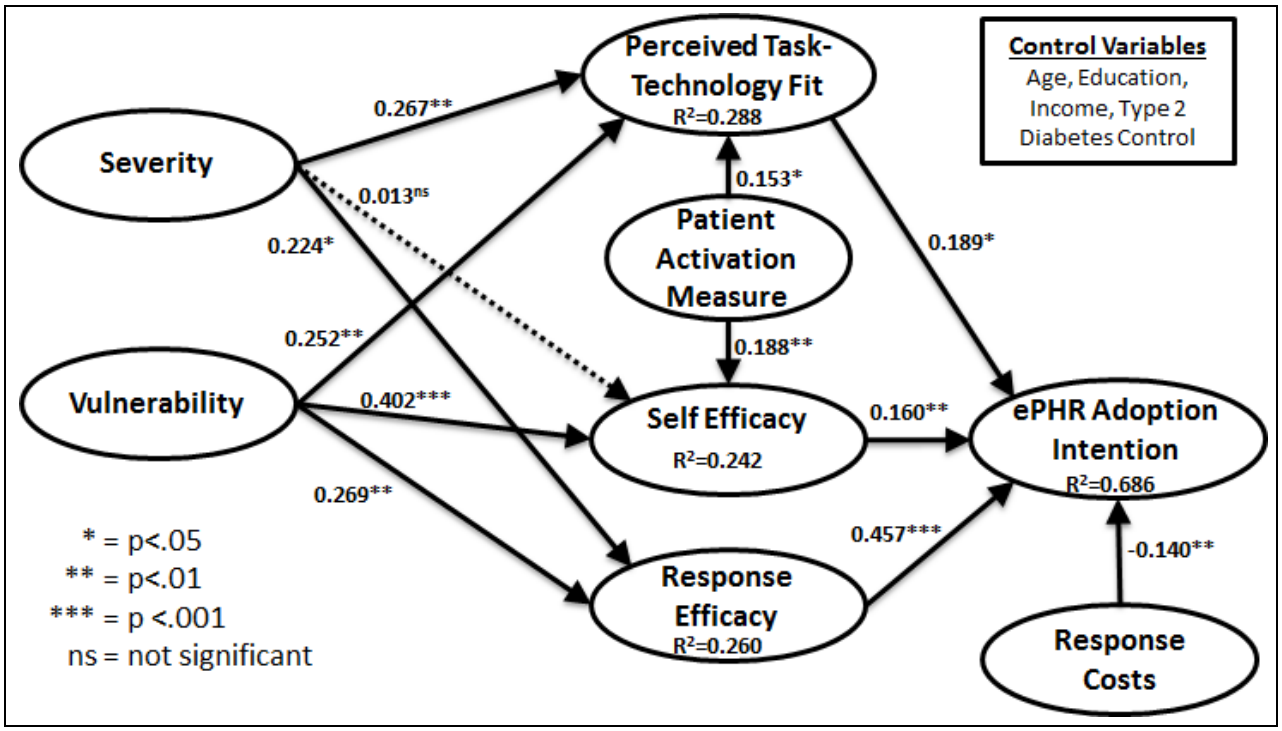


Figure 12 – Final PLS Model Results

Control Variables

Research has noted that the "effects of statistically controlling for confounding variables in non-experimental studies have received insufficient attention" (Breaugh, 2008, p. 282). Therefore this research followed the practices of other Information Systems (IS) studies and has included a number of variables to control for results that may be due to extraneous factors (Archer & Cocosila, 2011; Herath &

Rao, 2009a; Zhang, et al., 2011). As discussed previously, this research captured a number of demographic, Type 2 Diabetes specific and general health control variables. Rather than including all of these control variables in the research model, a more conservative approach was taken. Specifically, bivariate correlations were calculated to understand which of the control variables had a significant relationship with one or more of the endogenous variables in the model. The results of this analysis, shown in Table 30 indicate that Age, Income and Education each have one or more significant relationships with endogenous constructs in the model. The remaining control variables did not show significant relationships and therefore their inclusion as control variables in the model may not be warranted as they would have little to no effect on the endogenous constructs. In an effort to be thorough, a PLS model with all of the control variables was also analyzed to determine if any of the paths from the control variables to one or more of the endogenous constructs in the model was significant. The model included all of the control variables together in the model at the same time, as these control variables do not act in isolation (e.g., the effects of age and gender occur together, not separately). The results of this analysis, shown in Table 31 indicate that Age, Income and Type 2 Diabetes Control each have one or more significant paths to the endogenous constructs in the model. Therefore, the research model has included Age, Education, Income and Type 2 Diabetes Control as control variables, to ensure that the effects of these extraneous variables are controlled for.

Table 30 – Control Variable and Endogenous Construct Bivariate Correlations

		ADOPT	RE	SE	PTTF
AGE	Pearson Correlation	**-.251****	**-.254****	**-.208****	**-.235****
	Sig. (2-tailed)	**0.000**	**0.000**	**0.001**	**0.000**
	N	230	230	230	230
GENDER	Pearson Correlation	-0.067	-0.013	-0.022	-0.029
	Sig. (2-tailed)	0.313	0.839	0.742	0.660
	N	230	230	230	230
T2KNOWLEDGE	Pearson Correlation	-0.029	-0.077	-0.021	-0.034
	Sig. (2-tailed)	0.663	0.243	0.754	0.613
	N	229	229	229	229
T2CONTROL	Pearson Correlation	-0.052	-0.060	-0.003	0.019
	Sig. (2-tailed)	0.437	0.369	0.965	0.774
	N	229	229	229	229
T2DURATION	Pearson Correlation	-0.043	-0.091	-0.076	0.006
	Sig. (2-tailed)	0.515	0.171	0.252	0.924
	N	227	227	227	227
INCOME	Pearson Correlation	**.160***	0.097	**.141***	0.08
	Sig. (2-tailed)	**0.022**	0.169	**0.045**	0.256
	N	203	203	203	203
EDUCATION	Pearson Correlation	**.134***	0.080	0.105	0.082
	Sig. (2-tailed)	**0.043**	0.227	0.113	0.219
	N	227	227	227	227
GENERALHEALTH	Pearson Correlation	0.082	0.072	0.100	0.072
	Sig. (2-tailed)	0.223	0.280	0.136	0.281
	N	225	225	225	225
HEALTHKNOWLEDGE	Pearson Correlation	-0.040	-0.079	-0.004	-0.064
	Sig. (2-tailed)	0.553	0.241	0.950	0.340
	N	225	225	225	225

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 31 – PLS Model Control Variable Analysis

Control Variable	Construct	Path	Sig.	Control Variable	Construct	Path	Sig.
AGE	ADOPT	-0.040	1.223	**INCOME**	ADOPT	**0.076**	**2.235** *
	PTTF	**-0.176**	**2.949** **		PTTF	-0.018	0.363
	RE	**-0.159**	**2.688** **		RE	0.035	0.723
	SE	-0.128	1.958		SE	0.051	0.928
EDUCATION	ADOPT	0.032	0.955	**T2CONTROL**	ADOPT	-0.033	0.962
	PTTF	-0.018	0.413		PTTF	**0.196**	**2.871** **
	RE	-0.013	0.293		RE	0.120	1.774
	SE	-0.002	0.044		SE	0.101	1.523
GENDER	ADOPT	-0.053	1.514	**T2DURATION**	ADOPT	0.023	0.758
	PTTF	-0.054	1.201		PTTF	0.025	0.636
	RE	-0.050	1.131		RE	-0.069	1.312
	SE	-0.052	1.120		SE	-0.075	1.360
GH	ADOPT	-0.012	0.366	**T2KNOWLEDGE**	ADOPT	0.016	0.573
	PTTF	0.024	0.541		PTTF	-0.126	1.838
	RE	0.095	1.627		RE	-0.092	1.511
	SE	0.071	1.174		SE	-0.105	1.561
HK	ADOPT	0.008	0.245				
	PTTF	-0.022	0.452				
	RE	0.002	0.047				
	SE	-0.031	0.543				

The four control variables included in the research model revealed some significant paths when included together in the final research model. Table 32 provides details of the four control variables that were included in the final research model (note: in an effort to ensure the simplicity of structural model graphical results, these path coefficients are not shown in Figure 12). The results indicate that Age has a significant negative relationship with the PMT adaptive response variables (i.e., SE and RE), as well as a significant negative relationship with PTTF, indicating that as people age they report lower scores for SE, RE and PTTF. Conversely, Income has a significant positive relationship with ePHR Adoption Intention, indicating that people with higher incomes are more likely to adopt an ePHR. Finally, Type 2 Diabetes Control showed a significant positive relationship with PTTF and RE, indicating that people who feel they have better control over their Type 2 Diabetes exhibited stronger perceptions that the ePHR technology fit the task of self-management and that the ePHR could lead to better disease self-management.

Table 32 – PLS Model Final Control Variable Analysis

	Path	Significance	
AGE → ADOPT	-0.032	1.114	ns
AGE → PTTF	-0.174	3.001	<.01
AGE → RE	-0.183	3.219	<.01
AGE → SE	-0.155	2.500	<.05
EDUCATION → ADOPT	0.035	1.039	ns
EDUCATION → PTTF	-0.030	0.656	ns
EDUCATION → RE	-0.008	0.185	ns
EDUCATION → SE	-0.005	0.102	ns
INCOME → ADOPT	0.068	2.114	<.05
INCOME → PTTF	-0.010	0.211	ns
INCOME → RE	0.043	0.874	ns
INCOME → SE	0.059	1.091	ns
T2CONTROL->ADOPT	-0.033	1.061	ns
T2CONTROL → PTTF	0.152	2.450	<.05
T2CONTROL → RE	0.118	1.984	<.05
T2CONTROL → SE	0.077	1.339	ns

To assess the impacts of including these control variables in the model, a PLS analysis was completed for the research model, with no control variables included. The results of this analysis are presented in Figure 13 and Table 33. These results indicate that most of the variance in the model is captured by the theoretical constructs and only a small portion (i.e., 1.1%) is due to the control variables. The difference in variances between the two models (i.e., with and without control variables) indicates that the control variables have only a small effect sizes. In addition, none of the paths changed their algebraic sign, nor did any of the paths become non-significant. Therefore, the inclusion of the control variables is warranted, as they ensure that these extraneous factors are accounted for in the research model, yet they do not significantly change the impacts of the theoretical constructs.

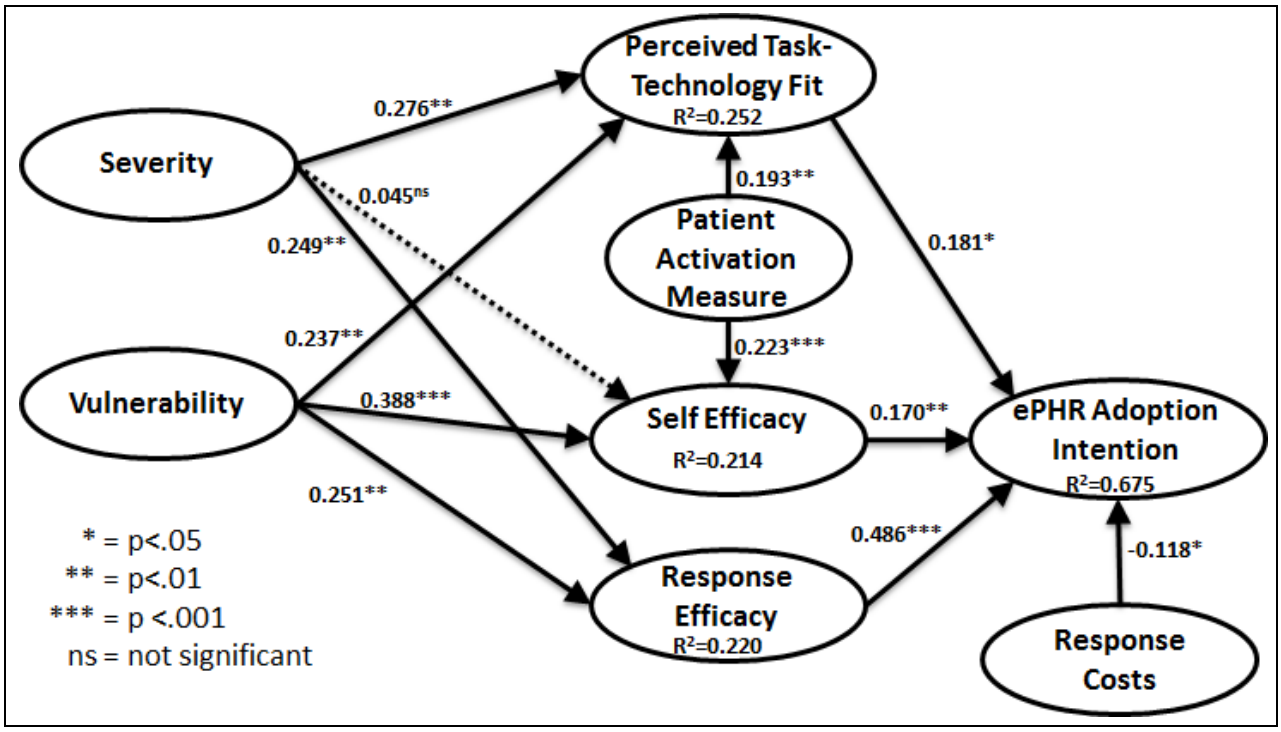


Figure 13 – PLS Model Results (No Control Variables)

PLS Model Results

As the focus of PLS analyses is prediction, an examination of the variance of the dependent variables through the R^2 results is the first recommended step (Chin, 2010; Roldán & Sánchez-Franco, 2012). As described by Roldán & Sánchez-Franco (2012), "The R^2 value represents a measure of the predictive power and indicates the amount of variance in the construct in question, which is explained by its antecedent variables in the model. The R^2 values should be high enough for the model to achieve a minimum level of explanatory power" (p. 205). Thresholds for R^2 vary in the literature, with some authors suggesting a minimum of 0.1 (Falk & Miller, 1992), while Chin (1998) suggests R^2 values of 0.67 as substantial, 0.33 as moderate and 0.19 as a minimum. Based on each of these thresholds, all of the R^2 values in this research study meet the minimum explanatory power requirements, as shown in Table 33. Most importantly, the endogenous variable in this study (i.e., ePHR Adoption Intention) exceeds the substantial threshold as per Chin (1998), indicating substantial explanatory power.

Table 33 - R^2 Results

Endogenous Construct	With Control Variables	Without Control Variables	Change	
	R^2	R^2	$f2$	Effect Size
PHR Adoption Intention (ADOPT)	0.686	0.675	.035	small
Perceived Task Technology Fit (PTTF)	0.288	0.252	.051	small
Self-Efficacy (SE)	0.242	0.214	.037	small
Response-Efficacy (RE)	0.260	0.220	.054	small

As a next step, an assessment of the individual path estimates (standardized regression coefficients) was completed. In this analysis, an examination of the algebraic signs (i.e., positive or negative) as well as the magnitude and significance of the path coefficients was completed. The results of the path estimate analysis and whether the hypothesized relationships were supported is shown in Table 34. The t-statistics were produced through the bootstrap method, with the number of cases parameter equal to the number of observations in the sample (i.e., 230). While some earlier literature has suggested the number of samples be set to 500 (described in Roldán & Sánchez-Franco, 2012), recent literature suggests that this value be increased to 5,000 (Hair, et al., 2011). Therefore, the number of samples used in this analysis was set to 5,000. In addition, the sign changes parameter was set to 'individual sign changes' as per Henseler et al. (2009). Given that all of the hypotheses have postulated a direction (i.e., a positive or negative relationship), a one-tailed t-test can be used (Roldán & Sánchez-Franco, 2012). Based on 230 observations (therefore 229 degrees of freedom), the critical t-values are: $p < 0.05$ (t=1.653), $p < 0.01$ (t= 2.343) and $p < 0.001$ (t= 3.127). However, both the one-tailed and two-tailed t-statistics have been included, as most previous studies use two-tailed tests. For two-tailed tests, the critical t-values are: $p < 0.05$ (t=1.971), $p < 0.01$ (t= 2.598) and $p < 0.001$ (t= 3.334).

As shown in Table 34, all but one (i.e., H6b) of the twelve hypothesized relationships was supported. For all hypotheses, the algebraic sign (i.e., either positive or negative) of the path coefficient matched the hypothesized algebraic sign. In addition, the results of the indirect effects that PAM, SEV and VUL have on ADOPT are included in Table 35, and show that all three of these variables have significant, positive indirect effects on ePHR Adoption Intention.

Table 34 – PLS Path Analysis (Direct Effects)

Hypothesis	Relationship	Path Coefficient	Hypothesized + / -	T-Statistic	Significance		Hypothesis Supported?
					1-Tail	2-Tail	
H1	**RE → ADOPT**	0.457	+	5.872	<.001	<.001	YES
H2	**SE → ADOPT**	0.160	+	2.600	<.01	<.01	YES
H3	**PTTF → ADOPT**	0.189	+	2.582	<.01	<.05	YES
H4	**RC → ADOPT**	-0.140	-	2.777	<.01	<.01	YES
H5a	**PAM → PTTF**	0.153	+	2.376	<.01	<.05	YES
H5b	**PAM → SE**	0.188	+	2.706	<.01	<.01	YES
H6a	**SEV → PTTF**	0.267	+	2.926	<.01	<.01	YES
H6b	**SEV →SE**	0.013	+	0.190	ns	ns	NO
H6c	**SEV → RE**	0.224	+	2.366	<.01	<.05	YES
H7a	**VUL → PTTF**	0.252	+	2.853	<.01	<.01	YES
H7b	**VUL → SE**	0.402	+	3.813	<.001	<.001	YES
H7c	**VUL → RE**	0.269	+	2.861	<.01	<.01	YES

Table 35 – PLS Path Analysis (Indirect Effects)

Relationship	Indirect Effect	T-Statistic	Significance	
			1-Tail	2-Tail
PAM → ADOPT	0.059	2.362	<.01	<.05
SEV → ADOPT	0.155	2.180	<.05	<.05
VUL → ADOPT	0.235	3.264	<.001	<.01

Effect Sizes

To evaluate the impact that antecedent (independent) constructs have on the dependent constructs, an effect size analysis was completed. Effect sizes can be evaluated via Cohen's f^2 (Cohen, 1988), which is calculated as follows:

$$f^2 = \frac{(R^{2\,(\text{included})} - R^{2\,(\text{excluded})})}{(1 - R^{2\,(\text{included})})}$$

To complete the analysis, R^2 (included) was the R^2 value calculated with the independent construct included, and R^2 (excluded) was the R^2 value calculated with the independent construct omitted. These values were then used in the f^2 calculation. To determine if the predictor (independent) construct has a small, medium or large effect size on the criterion (dependent) construct, the values of 0.02 (small), 0.15 (medium) and 0.35 (large) were used (Roldán & Sánchez-Franco, 2012). The results of this analysis have been included in Table 36, and shown graphically in Figure 14, and indicate that all but one of the effect

sizes is considered to be small (or nonsignificant for SEV→SE). Only RE→ADOPT shows a medium effect size. The majority of effect sizes being small is not surprising, as prior literature has shown that effect sizes in social science research are often small (Ferguson, 2009; Rosnow & Rosenthal, 2003).

Table 36 – PLS Effect Size Analysis

Dependent Construct	Independent Construct	R^2 Included	R^2 Excluded	ΔR^2	f^2	Effect Size	F-Test	P-Value
ADOPT	PTTF	0.686	0.674	0.012	0.038	small	8.599	0.004
	SE		0.674	0.012	0.038	small	8.599	0.004
	RE		0.626	0.060	0.191	medium	42.994	0.000
	RC		0.671	0.015	0.048	small	10.748	0.001
PTTF	PAM	0.288	0.269	0.019	0.027	small	6.031	0.015
	SEV		0.261	0.027	0.038	small	8.570	0.004
	VUL		0.262	0.026	0.037	small	8.253	0.004
SE	PAM	0.242	0.213	0.029	0.038	small	8.646	0.004
	SEV		0.242	0.000	0.000	ns	0.000	N/A
	VUL		0.176	0.066	0.087	small	19.678	0.000
RE	SEV	0.260	0.241	0.019	0.026	small	5.828	0.017
	VUL		0.230	0.030	0.041	small	9.203	0.003

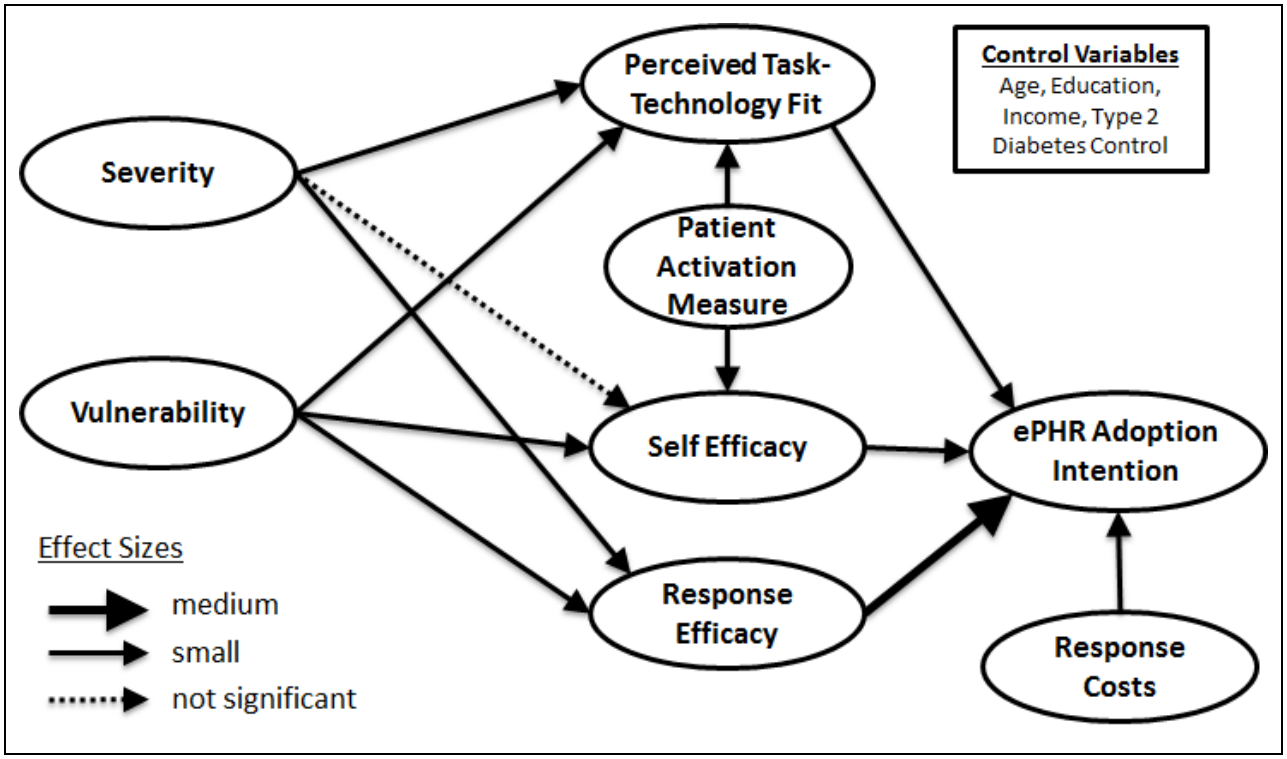


Figure 14 – PLS Model Effect Sizes

Goodness of Fit

PLS path modelling does not involve the use of multiple overall fit indices (as are available in covariance-based structural equation modelling (CBSEM)). However, a global goodness of fit index, or *GoF* index was proposed by Tenenhaus et al. (2004). As described by Vinzi et al. (2010a) "Such an index has been developed in order to take into account the model performance in both the measurement and the structural model and thus provide a single measure for the overall prediction performance of the model. For this reason the *GoF* index is obtained as the geometric mean of the average communality index and the average R^2 value" (p. 58). The *GoF* index formula is calculated as:

$$GoF = \sqrt{(\text{Average Communality} * \text{Average } R^2)}$$

This produces a value between zero and one, which can be interpreted similar to the interpretation of effect sizes, as per Wetzels et al. (2009), with thresholds for effect sizes as follows:

- *GoF* small (between 0.10 and 0.25)
- *GoF* medium (between 0.25 and 0.36)
- *GoF* large (greater than 0.36)

It is recommended that only latent variables with multi-item measurements be included in the *GoF* index calculations, as "single-item measurement always implies a communality of one, which means that it does not permit to quantify the measurement error in the indicator. Since the communality in case of single-item measurement is not informative about validity, it should not be considered when calculating the *GoF*." (Henseler & Sarstedt, 2012, p. 6). Therefore, the communality for PAM was not included in these calculations. Also, recent research indicates that the *GoF* index can be used for formative models (Vinzi, et al., 2010b), specifically "communalities may be also computed and interpreted in case of formative models knowing that, in such a case, we expect lower communalities but higher R^2 as compared to reflective models. Therefore, for practical purposes, the *GoF* index can be interpreted also with formative models as it still provides a measure of overall fit." (p. 58). Table 37 details the *GoF*

index calculation for this model. Given the *GoF* index value for this study is 0.495 (see Table 37), this indicates a large effect and therefore supports the conclusion that this model performs well.

Table 37 – GoF Index Calculation

	Communality	R^2
ADOPT	0.915	0.686
PTTF	0.743	0.288
RC	0.249	
RE	0.777	0.260
SE	0.554	0.242
SEV	0.602	
VUL	0.798	
Average	0.663	0.369
GoF Index	0.495	

In addition, a recently introduced Relative *GoF* index (Henseler & Sarstedt, 2012; Vinzi, et al., 2010b) commonly denoted as GoF_{rel}, was calculated. The formula for GoF_{rel} is:

$$GoF_{\text{rel}} = \sqrt{\text{Average } (\text{Communality}_{\text{PLS}}/\text{Communality}_{\text{PCA}})^* \text{ Average } (R^2_{\text{PLS}}/R^2_{\text{CanCor}})}$$

** Note PCA = Principal Components Analysis; CanCor = Canonical Correlation*

As per Vinzi et al. (2010b) "a value of the relative *GoF* equal to or higher than 0.90 clearly speaks in favour of the model." (p. 59). SPSS version 20 was used to calculate the $\text{Communality}_{\text{PCA}}$ and R^2_{CanCor} values (note the 'manova' syntax command was used to calculate R^2_{CanCor} values, as this feature is not available through the SPSS point and click boxes). Table 38 below provides the calculation of the GoF_{rel} and given the 0.992 value, the GoF_{rel} analysis provides strong support for the fit of this model to the data.

Table 38 – GoF_{rel} Calculation

	Communality			R^2		
	PLS	**PCA**	**PLS/PCA**	**PLS**	**CanCor**	**PLS/CanCor**
ADOPT	0.915	0.743	1.232	0.686	0.677	1.013
PTTF	0.743	0.773	0.962	0.288	0.280	1.029
RC	0.249	0.312	0.798			
RE	0.777	0.823	0.944	0.260	0.243	1.071
SE	0.554	0.691	0.802	0.242	0.249	0.972
SEV	0.602	0.745	0.807			
VUL	0.798	0.667	1.197			
Average			0.963			1.021
GoF_{rel} Index	0.992					

6.4.4 Educational Interventions

Diabetes Complications Education

A secondary objective of this research was to study the effects that educational interventions had on various constructs in the research model. Accordingly (as described previously), a portion of the respondents received education/information regarding the complications of Type 2 Diabetes, specifically Groups 1 and 2 (DC=0, n=120) received no Diabetes Complications (DC) education while Groups 3 and 4 (DC=1, n=110) received intense DC education. The research design included manipulation check questions, which were asked after the viewing of the DC video clips and after responses to the SEV and VUL constructs had been recorded. The three DC manipulation check questions were:

MCDC1. The video clip increased my level of concern about the severity of my Type 2 Diabetes.
MCDC2. The video clip increased my level of concern about my vulnerability to complications that may arise from my Type 2 Diabetes.
MCDC3. The video clip increased my level of concern about current and future health threats posed by my Type 2 Diabetes condition and the associated complications.

A one-way ANOVA analysis was conducted to ascertain if there were significant differences between the responses to the manipulation check questions between Groups 1 and 2 (who viewed the unrelated Frederick Banting Museum video) and Groups 3 and 4 (who viewed the intense DC video). The results of this analysis, shown in Table 39, clearly indicate that Groups 3 and 4 assessed the video they viewed as

much more intense (i.e., it increased their levels of concern about Severity, Vulnerability and health threats from their Type 2 Diabetes) as compared to Groups 1 and 2, as shown by the significant differences in the mean responses to the manipulation check questions. Therefore, the manipulation check indicates the treatment was effective.

Table 39 – One-Way ANOVA Analysis for DC Education Manipulation Check Items

		n	Mean	SD	95% Confidence Interval for Mean		ANOVA (Between Groups)			
					Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
MCDC1	None	120	4.23	1.393	3.97	4.48	75.60	75.60	41.772	**0.000**
	Intense	110	5.37	1.291	5.13	5.62				
	Total	230	4.77	1.460	4.58	4.96				
MCDC2	None	120	4.30	1.476	4.03	4.57	69.44	69.44	36.182	**0.000**
	Intense	110	5.40	1.279	5.16	5.64				
	Total	230	4.83	1.488	4.63	5.02				
MCDC3	None	120	4.34	1.464	4.08	4.61	66.51	66.51	35.122	**0.000**
	Intense	110	5.42	1.273	5.18	5.66				
	Total	230	4.86	1.475	4.66	5.05				

Next, an examination of the constructs that the video clips were intended to manipulate (i.e., SEV and VUL) via a one-way ANOVA was performed. The results of this analysis, shown in Table 40 indicate that the mean answers for respondents in Groups 3 and 4 (who viewed the intense DC video) were not significantly different than the answers for respondents in Groups 1 and 2 for the constructs in question (i.e., SEV and VUL), and therefore Hypotheses 8a (individuals receiving intense DC education will experience higher perceptions of SEV compared to individuals receiving no DC education) and 8b (individuals receiving intense DC education will experience higher perceptions of VUL compared to individuals receiving no DC education) were not supported. In fact, while not significantly different, the results for both SEV and VUL are in fact slightly lower for Groups 3 and 4, indicating these respondents reported lower responses to the SEV and VUL items. This unexpected result is discussed in more detail in Chapter 7.

Table 40 – One-Way ANOVA Analysis for DC Education (None versus Intense)

		n	Mean	SD	95% Confidence Interval for Mean		ANOVA (Between Groups)			
					Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	None	120	5.157	1.008	4.975	5.339				
	Intense	110	4.980	1.028	4.786	5.175	1.791	1.791	1.728	0.190
	Total	230	5.072	1.019	4.940	5.205				
VUL	None	120	5.415	1.083	5.219	5.610				
	Intense	110	5.321	1.096	5.113	5.528	0.509	0.509	0.428	0.513
	Total	230	5.370	1.088	5.228	5.511				

In addition to one-way ANOVA analysis, researchers can also complete a MANOVA analysis, which examines the effects of independent variables (i.e., in this research a DC education dummy variable) on a set of dependent variables (i.e., in this research SEV and VUL) collectively and simultaneously (Meyers, et al., 2006). In MANOVA analyses, the sets of dependent variables are combined into weighted linear composites (Meyers, et al., 2006). MANOVAs are important, as "single dependent measures seldom capture completely a phenomenon being scrutinized" (Meyers, et al., 2006, p. 367). It is important in a MANOVA analysis that it makes conceptual sense to package together the specific individual dependent variables (Maxwell, 2001). However, MANOVA analyses should not be used when the dependent variables are either uncorrelated or too highly correlated (Meyers, et al., 2006) with a threshold of correlations between 0.3 and 0.7 deemed acceptable (Maxwell, 2001). Correlations less than 0.3 indicate that the variables are not related, and correlations greater than 0.7 indicate redundancy (Maxwell, 2001). Therefore, while conceptually it makes sense to package the SEV and VUL constructs (collectively as a threat variable), the correlation between SEV and VUL is greater than 0.7, and thus a MANOVA analysis could not be completed.

ePHR Education

Similar to the DC education analysis described above, respondents also received different levels of education/information regarding the use and benefits of ePHRs. Groups 1 and 3 (ePHR=0, n=126) received basic ePHR education, while groups 2 and 4 (ePHR=1, n=104) received advanced ePHR

education. The research design included manipulation check questions, which were asked after the viewing of the ePHR education video clip and after responses to the ADOPT, PTTF, RE, SE, PAM and RC constructs had been recorded. The three ePHR education manipulation check questions were:

MCPHR1. After watching the video clip about ePHRs, I feel I have a better understanding of how to use an ePHR to assist in the self-management of my Type 2 Diabetes.

MCPHR2. After watching the video clip about ePHRs, I feel I have a better understanding about the benefits of using an ePHR to assist in the self-management of my Type 2 Diabetes.

MCPHR3. After watching the video clip about ePHRs, I feel more confident that I would be able to use an ePHR to assist in the self-management of my Type 2 Diabetes.

A one-way ANOVA analysis was conducted to ascertain if there were significant differences between the responses to the manipulation check questions between the Groups 1 and 3 who viewed the basic ePHR education video clip and Groups 2 and 4 who viewed the advanced ePHR education video clip. The results of this analysis (see Table 41) indicate that Groups 2 and 4 assessed the video they viewed as providing greater levels of understanding of how to use an ePHR for Type 2 Diabetes self-management, the benefits of using an ePHR for Type 2 Diabetes self-management and more confidence in their abilities to use an ePHR for Type 2 Diabetes self-management as compared to Groups 1 and 3 (who received only basic ePHR education), as shown by the significant differences in the mean responses to the manipulation check questions. Therefore, the manipulation check indicates the treatment was effective.

Table 41 – One-Way ANOVA Analysis for ePHR Education Manipulation Check Items

					95% Confidence Interval for Mean		ANOVA (Between Groups)			
		n	Mean	SD	Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
MCPHR1	Basic	126	4.86	1.198	4.65	5.07				
	Advanced	104	5.67	1.194	5.44	5.91	37.93	37.93	26.502	**0.000**
	Total	230	5.23	1.261	5.06	5.39				
MCPHR2	Basic	126	4.98	1.084	4.79	5.17				
	Advanced	104	5.61	1.092	5.39	5.82	22.58	22.58	19.096	**0.000**
	Total	230	5.26	1.130	5.11	5.41				
MCPHR3	Basic	126	4.96	1.120	4.76	5.16				
	Advanced	104	5.44	1.261	5.20	5.69	13.24	13.24	9.427	**0.002**
	Total	230	5.18	1.207	5.02	5.34				

Next, an examination of the constructs that the ePHR education video clips were hypothesized to directly manipulate (i.e., RE, PTTF, SE) was performed. The results of this analysis, shown in Table 42 indicate that the mean of the responses for respondents in Groups 2 and 4 (who viewed the advanced ePHR education video) were significantly different (i.e., higher) than the answers for respondents in Groups 1 and 3 for two (i.e., SE and PTTF) of the three constructs the ePHR education was hypothesized to manipulate. In addition, the mean of the responses for the third construct the ePHR education was hypothesized to manipulate (i.e., RE) was close to significant (i.e., 0.072). Therefore Hypotheses 9b (individuals receiving advanced ePHR education will experience higher perceptions of SE compared to individuals receiving basic ePHR education) and 9c (Individuals receiving advanced ePHR education will experience higher perceptions of PTTF compared to individuals receiving basic ePHR education) are supported. Hypothesis 9a (individuals receiving advanced ePHR education will experience higher perceptions of RE compared to individuals receiving basic ePHR education), while not supported at the $p<0.05$ level is supported at the $p<0.10$ level. Recent IS literature (from well-known IS researchers) appearing in top journals and conferences has begun to note what is sometimes referred to as 'modest' or 'marginal' significance ($0.10 < p < 0.05$) (e.g., Dimoka & Davis, 2008; Dimoka, et al., 2012; Hong & Pavlou, 2010). Thus (and in line with the above noted research) the differences in RE between the two groups receiving different levels of ePHR education can be considered marginally significant.

Table 42 – One-Way ANOVA Analysis for ePHR Education Levels (Basic versus Advanced)

					95% Confidence Interval for Mean		ANOVA (Between Groups)			
		n	Mean	SD	Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
RE	Basic	126	5.337	0.902	5.178	5.496	2.828	2.828	3.276	0.072
	Advanced	104	5.560	0.961	5.373	5.747				
	Total	230	5.438	0.934	5.317	5.559				
PTTF	Basic	126	5.140	0.876	4.986	5.295	5.536	5.536	7.187	**0.008**
	Advanced	104	5.452	0.880	5.281	5.623				
	Total	230	5.281	0.889	5.166	5.397				
SE	Basic	126	5.056	0.927	4.892	5.219	3.691	3.691	4.363	**0.038**
	Advanced	104	5.310	0.911	5.133	5.487				
	Total	230	5.171	0.927	5.050	5.291				

In addition to the univariate ANOVA analysis completed, a multivariate (i.e., MANOVA) analysis of the relationships between the ePHR education and the RE and SE constructs (i.e., the efficacy variates) was completed. As mentioned previously, MANOVA analyses should not be used when the dependent variables are either uncorrelated or too highly correlated (Meyers, et al., 2006). Therefore, while conceptually it made sense to package RE, SE and PTTF (as the efficacy variables), the correlations between RE and PTTF were greater than 0.7, and thus a MANOVA analysis was only completed with SE and RE (PMT efficacy variables) as the 'packaged' dependent variable. For this analysis, RE and SE form the dependent variable with a dummy variable representing the ePHR educational intervention as the independent. The key results from this analysis are included in Table 43. First, the non-significant Box's Test of Equality of Covariance Matrices (i.e., 0.704) indicates that the covariance matrices of the dependent variables are equal across the levels of the independent ePHR dummy variable, a requirement for MANOVA analyses. Second, the significant Bartlett's Test of Sphericity (i.e., 0.000) indicates that there is sufficient correlation between the dependent variables to move forward with the multivariate analysis. The results of the multivariate analysis show that the multivariate effect of ePHR on RE and SE, or collectively the efficacy variate is close to significant (i.e., 0.10), indicating that group differences on the dependent variate may exist, but given the lack of statistical significance, this cannot be stated with the required level of certainty.

Table 43 – Multivariate MANOVA Analysis of RE and SE by ePHR

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
1.422	.469	3	50,505,347.462	**.704**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	133.192	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.975	4,509.95[b]	2	227	.000	.975
	Wilks' Lambda	.025	4,509.95[b]	2	227	.000	.975
	Hotelling's Trace	39.735	4,509.95[b]	2	227	.000	.975
	Roy's Largest Root	39.735	4,509.95[b]	2	227	.000	.975
ePHR	Pillai's Trace	.020	2.328[b]	2	227	.100	.020
	Wilks' Lambda	.980	2.328[b]	2	227	.100	.020
	Hotelling's Trace	.021	2.328[b]	2	227	.100	.020
	Roy's Largest Root	.021	2.328[b]	2	227	.100	.020

a. Design: Intercept + ePHR

b. Exact statistic

6.4.5 Post-Hoc Analyses

This section examines the combination effects of the educational interventions that were discussed above, the relevance of any additional non-hypothesized relationships in the research model, and presents a thorough control variable analysis to complete research objective number four (see Section 1.3).

Educational Intervention Individual Group Comparisons

As discussed in Chapter 5, participants were randomly placed into one of four groups, and received different combinations of educational interventions via the video clips:

Group1 → DC=none, ePHR=Basic

Group2 → DC=none, ePHR=Advanced

Group3 → DC=Intense, ePHR=Basic

Group4 → DC=Intense, ePHR=Advanced

In Section 6.4.4 above, an analysis of the larger educational intervention groupings was completed. However, participants in this research received a combination of DC education and ePHR education, and therefore an analysis of the potential combination effects of the educational interventions was completed. Given the number of respondents in each group, it was not possible to generate PLS models for each group due to sample size limitations (i.e., each group would require 60 participants). However, sample sizes were sufficient to perform an ANOVA analysis. A one-way ANOVA analysis that examines the differences in means for the four groups was completed, with the results included in Table 44. The results of this analysis indicate that there were significant differences between the groups in the responses for RE, PTTF and SE.

Table 44 – One-Way ANOVA Group Comparisons

	Sum of Squares	df	Mean Square	F	Sig.
SEV	3.55	3	1.183	1.140	0.334
VUL	1.37	3	0.455	0.381	0.767
ADOPT	2.89	3	0.964	0.657	0.579
RE	**6.65**	**3**	**2.215**	**2.593**	**0.053**
PTTF	**7.20**	**3**	**2.398**	**3.116**	**0.027**
SE	**6.29**	**3**	**2.098**	**2.491**	**0.061**
PAM	433.00	3	144.277	0.570	0.636
RC	6.79	3	2.263	1.609	0.188

In order to assess which groups exhibited significant differences in the responses for RE, PTTF and SE, a Tukey's HSD (Honestly Significant Differences) was also completed part of the one-way ANOVA. The Tukey's HSD is a post-hoc analysis that compares all possible pairs of means, and identifies where there are significant differences. Full details of this analysis are included in Appendix O, with Table 45 providing details for only those pairs of means which were found to be significantly different. The results of the Tukey's HSD analysis indicate that Group 2 and Group 3 showed significant differences for the means of the RE, SE and PTTF constructs. All other mean differences between groups for the other constructs were found to be non-significant. This analysis indicates that the responses for the PTTF, RE

and SE constructs were significantly higher for Group 2 (no DC education, advanced ePHR education) than for Group 3 (intense DC education, basic ePHR education).

Table 45 – One-Way ANOVA Group Comparison Significant Results

Construct	Group 2 Mean	Group 3 Mean	Mean Difference	Sig.
RE	5.715	5.258	0.457	.037
PTTF	5.532	5.058	0.474	.018
SE	5.421	4.964	0.457	.035

Additional Relationships

In an effort to examine potentially significant paths that were not hypothesized, an analysis of a model containing additional relationships was conducted. The paths that were added followed the flow of the OPMT model, in that additional relationships were added from the left side of the model (threat variables) to the right side of the model (efficacy and behaviour variables). In addition, given the hypothesized relationships between PAM→PTTF and PAM→SE, additional paths to the other PMT variables (i.e., PAM→SEV, PAM→VUL, PAM→RE and PAM→RC), as well as PAM→ADOPT were added. Table 46 details the results of the additional paths that were added to the model. As the results in Table 46 indicate, only one of these additional nine paths (i.e., VUL→RC) was significant (bootstrapping, 230 cases, 5,000 samples) using a two-tailed t-test. In addition, there was a slight decrease in R^2 for the endogenous variable (i.e., ePHR Adoption Intention dropped from 0.686 to 0.682). A thorough literature review found no support for the relationship between VUL→RC, nor is there a logical reason to hypothesize a path between these two variables. Therefore, it is reasonable to presume that the original research model includes all of the key relationships between the constructs, and none of these additional paths warrants inclusion in the model.

Table 46 – Additional Relationships Analysis

Independent	Dependent	Path Coefficient	T-Statistic	Significance*
SEV →	RC	0.081	.945	ns
	ADOPT	-0.019	.515	ns
VUL →	RC	**-0.243**	**2.332**	**< 0.05**
	ADOPT	0.043	1.001	ns
PAM →	SEV	-0.039	0.753	ns
	VUL	-0.002	0.051	ns
	RE	0.075	1.358	ns
	RC	-0.076	0.992	ns
	ADOPT	0.026	0.846	ns

** ns = not significant*

Detailed Control Variable Analysis

As detailed earlier, a number of control questions, including demographic, Type 2 Diabetes specific and general health questions were included as part of the survey. An analysis of how these interact with the constructs as well as the research model was conducted. In order to thoroughly evaluate the effects of the control variables, multiple different statistical analyses were completed:

1. Bivariate correlation analysis, examining the correlations between each of the control variables with each of the endogenous constructs in the model (see Table 30).
2. A one-way ANOVA analysis (that examined the differences between control variable groupings) for all constructs (see Appendix P and Table 48).
3. MANOVA analyses that examined the effects of the control variables on the 'packaged variable' of RE and SE (see Appendix P and Tables 49 and 50).
4. A PLS analysis that examined the effects of adding all of the control variables to the model at the same time (see Table 31).
5. A PLS analysis that examined the effects of adding the control variables to the model one at a time (see Appendix Q and Table 51).

As described previously and detailed in Table 30, a bivariate correlation analysis was completed, examining the correlations between each of the control variables with each of the endogenous constructs (therefore not with SEV, VUL, PAM or RC) in the research model. The results of this analysis showed that AGE had significant negative correlations with ADOPT, PTTF, RE and SE, INCOME had significant positive correlations with ADOPT and SE, and EDUCATION had a significant positive correlation with ADOPT. None of the other correlations were significant.

In an effort to ensure that all relevant findings were revealed, one-way ANOVAs were run for all control variables, testing for significant mean differences between the control variable groups for all constructs in the model. Given the minimum sample size requirements detailed below in Table 47 required to detect a medium effect size (i.e., $f = 0.25$), with power = 0.8 and $\alpha = 0.05$ (Faul, et al., 2007), the control variable responses were combined into larger groups where necessary. All attempts were made to ensure that these larger groups met the minimum size requirements, and exhibited logic with respect to the groupings. The results of the one-way ANOVA analysis, including Tukey's HSD (Honestly Significant Differences) have been included in Appendix P, with a summary of the findings shown in Table 48.

Table 47– Minimum Sample Size Requirements – One-Way ANOVAs

Number of Groups	Total Sample Size	Minimum Number Required per Group
2	128*	64*
3	159	53
4	180	45
5	200	40
6	216	36

** 51 per group required for simple t-test, which can be conducted between only 2 groups (Faul, et al., 2007)*

Table 48 – One-Way ANOVA Results Summary

Demographics		
Age	Groupings: 1. 18-49 2. 50-59 3. 60-69 4. 70+	• Significant differences in the responses based on age for SEV, VUL, ADOPT, RE, SE, PTTF. In all cases the mean responses show a declining trend as respondent age increases. • Tukey's HSD Analysis: ▪ SEV - Significant differences between i) 18-49 and 60-69; ii) 18-49 and 70+; iii) 50-59 and 70+. ▪ VUL - Significant differences between i) 50-59 and 60-69; ii) 50-59 and 70+. ▪ ADOPT - Significant differences between i) 18-49 and 60-69; ii) 18-49 and 70+' iii) 50-59 and 70+. ▪ RE - Significant differences between i) 18-49 and 70+; ii) 50-59 and 70+. ▪ SE - Significant differences between i) 18-49 and 60-69; ii) 18-49 and 70+. ▪ PTTF - Significant differences between i) 18-49 and 70+ ii) 50-59 and 70+. For all significant differences noted above, respondents in the younger age category scored significantly higher than respondents in the older age category.
Gender	Groupings: 1. Female 2. Male	• No significant differences in the responses for any of the constructs based on gender.
Marital Status	Groupings: N/A	• Based on the insufficient number of respondents in each marital status category, and the inability to group respondents into meaningful larger groupings, the one-way ANOVA analysis was not completed based on marital status.
Education	Groupings: 1. Some College/ University or Less 2. College/ University Degree (includes Diplomas and Graduate Degrees)	• Significant differences in the responses based on education level for PAM, which indicates that respondents with higher levels of education reported higher PAM scores, showing a greater readiness for self-management.
Income	Groupings: 1. <$50,000 2. $50,000 - $75,000 3. $75,000 +	• Significant differences in the responses based on income level for PAM, which indicates that respondents with higher levels of income reported higher PAM scores, showing a greater readiness for self-management. • Tukey's HSD Analysis: ▪ PAM - Significant differences between <$50,000 and $75,000+ income categories, with higher income bracket (i.e., $75,000+) reporting significantly higher PAM scores than lower income bracket (i.e., <$50,000) respondents.
Employment Status	Groupings: N/A	• Based on the insufficient number of respondents in each employment category, and the inability to group respondents into meaningful larger groupings, the one-way ANOVA analysis was not completed based on employment status.

Type 2 Diabetes Factors		
Type 2 Diabetes Knowledge	Groupings: 1. Poor, Fair 2. Good 3. Very Good, Excellent	• Significant differences in the responses based on Type 2 Diabetes Knowledge for PAM, which indicates that respondents with higher levels of knowledge regarding their Type 2 Diabetes reported higher PAM scores, showing a greater readiness for self-management. • Tukey's HSD Analysis: ▪ PAM - Significant differences between Poor/Fair and Good, Poor/Fair and Excellent, as well as Good and Very Good/Excellent. In all cases, respondents who reported levels of Type 2 Diabetes Knowledge had significantly higher PAM scores.
Type 2 Diabetes Control	Groupings: 1. Very Poor, Poor, Moderate 2. Well, Very Well	• Significant differences in the responses based on Type 2 Diabetes Control for SEV, VUL and PAM which indicates respondents with higher reported levels of control over their Type 2 Diabetes: ▪ Reported lesser feelings of severity and vulnerability regarding their Type 2 Diabetes. ▪ Reported higher PAM scores, showing a greater readiness for self-management.
Type 2 Diabetes Duration	Groupings: 1. < 10 years 2. 10 + years	• No significant differences in the responses based on Type 2 Diabetes Duration (i.e., time since diagnosis) for any of the constructs.
General Health Factors		
General Health Condition	Groupings: 1. Poor, Fair 2. Good, Very Good, Excellent	• Significant differences in the responses based on self-reported general health condition for PAM and RC, which indicates respondents with higher self-reported levels of general health condition: ▪ Reported higher PAM scores, showing a greater readiness for self-management. ▪ Reported lower RC scores, indicating they did not deem the potential costs of an ePHR to be as high compared to those who self-reported lower levels of general health condition.
General Health Knowledge	Groupings: 1. Poor, Fair, Good 2. Very Good, Excellent	• Significant differences in the responses based on self-reported general health knowledge for PAM, RC, SEV and VUL which indicates that respondents with better self-reported levels of general health knowledge: ▪ Reported higher PAM scores, showing a greater readiness for self-management. ▪ Reported lesser feelings of severity and vulnerability regarding their Type 2 Diabetes. ▪ Reported lower scores on RC, indicating they did not deem the potential costs of an ePHR to be as high compared to those who reported lower levels of general health knowledge.

In addition to the one-way ANOVA analyses, MANOVA analyses were completed, which examined the effects of the control variables on sets of dependent variables collectively and simultaneously (Meyers, et al., 2006). Again, MANOVA analyses should not be used when the dependent variables are either uncorrelated or too highly correlated (Meyers, et al., 2006). Therefore,

while conceptually it made sense to package SEV and VUL (threat variables) and RE, SE and PTTF (efficacy variables), the correlations between SEV and VUL, as well as RE and PTTF were greater than 0.7, and thus MANOVA analyses were only completed with SE and RE (PMT efficacy variables) as the packaged dependent variables. The details of these analyses are included in Appendix P, and indicate that AGE was the only control variable that showed a significant multivariate effect on efficacy (i.e., RE and SE). Therefore the specific MANOVA results for AGE have been included as Table 49. First, the non-significant Box's Test of Equality of Covariance Matrices (i.e., 0.169) indicates that the covariance matrices of the dependent variables are equal across the levels of the independent AGE variable, a requirement for MANOVA analyses. Second, the significant Bartlett's Test of Sphericity (i.e., 0.000) indicates that there is sufficient correlation between the dependent variables to move forward with the multivariate analysis (Meyers, et al., 2006). The results of the multivariate analysis show that the multivariate effect of AGE on both SE and RE, or collectively the efficacy variate is significant, indicating that group differences on the dependent variate exist (Meyers, et al., 2006).

Table 49 – Multivariate MANOVA Analysis of RE and SE by AGE

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
20.907	1.339	15	12,418.026	**.169**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	125.457	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.965	3097.475[b]	2	223	.000	.965
	Wilks' Lambda	.035	3097.475[b]	2	223	.000	.965
	Hotelling's Trace	27.780	3097.475[b]	2	223	.000	.965
	Roy's Largest Root	27.780	3097.475[b]	2	223	.000	.965
AGE	Pillai's Trace	.163	3.965	10	448	**.000**	.081
	Wilks' Lambda	.843	3.981[b]	10	446	**.000**	.082
	Hotelling's Trace	.180	3.998	10	444	**.000**	.083
	Roy's Largest Root	.131	5.872[c]	5	224	**.000**	.116

a. Design: Intercept + AGE

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Given the significant multivariate results found for AGE, further statistical analyses were performed. First, a re-examination of the ANOVAs, using an adjusted alpha level (i.e., *Bonferroni correction*) was completed. Given an alpha level of 0.05 and 2 dependent variables, the value of 0.025 becomes the new and stricter alpha level which is used to evaluate the two dependent variables. As shown in Appendix P, all of the significance values for RE and SE in the ANOVA analysis for the AGE control variable (that were significant) are less than this stricter 0.025 level. Second, a Roy-Bargman Step-Down Analysis was completed. This analysis assesses each dependent variable separately, computing a univariate F-value after controlling for the effects of each remaining dependent measure in a process similar to hierarchical regression (Meyers, et al., 2006). If the dependent variables are correlated (which SE and RE are), and there is a logical priority of ordering, then the step-down analysis is the preferred analysis (Tabachnick & Fidell, 2006). For the SE and RE dependent variables, it is logical to

assume that SE would precede RE, as SE is the individual's assessment of their ability to use the ePHR (therefore the current time-frame) while RE is their assessment of the potential future effects of using the ePHR. The results of the Step-Down test are provided in Table 50 and indicate that there is unique variability in RE based on AGE even after the adjustment for SE has been made.

Table 50 - Roy-Bargman Step-Down F-Tests

Variable	Hypoth. MS	Error MS	StepDown F	Hypoth. DF	Error DF	Sig. of F
SE	3.210	.806	3.983	5	224	.002
RE	1.804	.451	3.998	5	223	.002

Finally, the effects of the control variables was assessed via PLS path modelling. As described previously and detailed in Table 31 all control variables were entered into the PLS model at the same time to understand the effects these control variables had in combination with the model constructs. The results of this analysis showed that AGE had significant negative relationships with PTTF and RE, INCOME has a significant positive relationship with ADOPT, and T2CONTROL has a significant positive relationship with PTTF.

In addition, an analyses was completed whereby each control variable was added one at a time into the PLS model, specifically adding a path from the control variable to each dependent variable in the model, and analyzing the path coefficients and R^2 values of the dependent variables as well as an effect size analysis. The details of this analysis are included in Appendix Q and summarized in Table 51, which provides the results (path coefficient, significance, effect size) only where significant path coefficients were found.

Table 51- Demographic Control Variable PLS Path Analysis

Control Variable	Construct	Path	Sig.	Effect Size
AGE	**PTTF**	-0.136	2.562 *	small
	RE	-0.167	3.075 **	small
	SE	-0.151	2.650 **	small
INCOME	**ADOPT**	0.085	2.800 **	small
T2DURATION	**RE**	-0.122	2.104 *	ns
	SE	-0.123	2.249 *	ns
GENERALHEALTH CONDITION	**RE**	0.121	2.300 *	ns

*Note: ns=not significant, *=p< .05, **=p< .01*

To help in the overall understanding of the control variables, a complete summary of all of the control variable analyses (i.e., correlation, ANOVA, MANOVA and PLS) is provided in Table 52. This summary serves to bring together the results of the multiple types of analyses to allow the reader a more holistic view of the impacts of the control variables, showing those that have been conclusively shown to have an effect on the variables in the research model. As the results demonstrate, AGE appears to be the most important control variable, as it has an effect on six of the constructs, and these results were confirmed through multiple analysis methods. From a construct perspective, PAM appears to be the most affected by the control variables, with six of the nine control variables showing significant effects on the PAM construct. SEV and VUL are the next most affected constructs, each having three control variables that have a significant effect on them. For all analyses which included a direction of the relationship (i.e., either positive or negative), the different analyses methods produced the same results for the relationship direction.

Table 52 – Control Variable Summary Analysis

Control Variable	SEV[1]	VUL[1]	ADOPT[2]	RE	SE	PTTF[2]	PAM[1]	RC[1]
Age	**↑ ↓ (ANOVA)**	**↑ ↓ (ANOVA)**	↑ ↓ (ANOVA, Correlation)	**↑ ↓ (ANOVA, Correlation MANOVA, PLS)**	**↑ ↓ (ANOVA, Correlation MANOVA, PLS)**	**↑ ↓ (ANOVA, Correlation, PLS)**		
Gender								
Education			↑ ↑ (Correlation)				**↑ ↑ (ANOVA)**	
Income			↑ ↑ (PLS, Correlation)		↑ ↑ (Correlation)		**↑ ↑ (ANOVA)**	
Type 2 Diabetes Knowledge							**↑ ↑ (ANOVA)**	
Type 2 Diabetes Control	**↑ ↓ (ANOVA)**	**↑ ↓ (ANOVA)**				↑ ↑ (PLS)	**↑ ↑ (ANOVA)**	
Type 2 Diabetes Duration				↑ ↓ (PLS)	↑ ↓ (PLS)			
General Health Condition				↑ ↑ (PLS)			**↑ ↑ (ANOVA)**	**↑ ↓ (ANOVA)**
General Health Knowledge	**↑ ↓ (ANOVA)**	**↑ ↓ (ANOVA)**					**↑ ↑ (ANOVA)**	**↑ ↓ (ANOVA)**

↑ ↓ indicates control variable and construct responses move in opposite direction
↑ ↑ indicates control variable and construct responses move in the same direction

- Items in parentheses indicate which analyses showed significant results
- bolded text indicate all completed analyses confirmed significant results
- grayed text indicate only some of the completed analyses confirmed significant results
- blank cells indicate none of the completed analyses showed significant results

1. Only ANOVA analysis was completed on SEV, VUL, PAM and RC as correlation, MANOVA and PLS analyses were not applicable.
2. No MANOVA analysis was completed on ADOPT and PTTF as this analysis was not applicable.

Chapter 7. Discussion and Conclusions

This chapter contains a discussion of the findings of this research, the contributions made by this research to both academics and practitioners, and limitations of this research. Some future directions for research in this area are also outlined.

7.1 Key Findings

As the worldwide prevalence of chronic disease increases, the need for people afflicted with chronic disease to self-manage their condition is becoming more important. ePHRs can benefit people with chronic diseases to accomplish the complex and time consuming task of self-management. However, ePHR adoption has been slow and limited research into the motivations behind adoption and use has been conducted. This current research addresses this gap by taking a new approach in combining health based theory and concepts with task focused Information Systems (IS) theory to understand the motivations behind the intention to adopt an ePHR for Type 2 Diabetes self-management.

This current research found that a combined model, which incorporates Ordered Protection Motivation Theory (OPMT) and the Patient Activation Measure (PAM) from the health research stream and Perceived Task-Technology Fit (PTTF) from the IS stream can be very helpful in understanding ePHR adoption intention and its antecedent constructs. The explanatory power of this combined model is very strong, with 68.6% of the variance in intention to adopt an ePHR explained by the model. Eleven of the twelve path coefficients in the combined model were significant, with the majority of these being significant at the $p < 0.01$ level.

The combined model developed and tested in this research supports the value and applicability of an ordered approach to PMT in the adoption intention of an ePHR. Specifically, people first assess the threat of their chronic disease and then assess the adaptive coping response elements available through the use of an ePHR, which in-turn lead to intention to adopt. This research suggests that higher perceptions of the threat from chronic disease are related to stronger beliefs that an ePHR technology can help in the self-management of an individual's chronic disease, that individuals will be able to use an ePHR and that the

ePHR technology is a good fit for the task of self-management. In addition, this research suggests that higher perceptions of these three elements (i.e., PTTF, SE and RE) are positively related to a person's intention to adopt an ePHR, with the potential costs of using an ePHR for self-management negatively related to the intention to adopt an ePHR.

People with Type 2 Diabetes appear to be very interested in adopting and using an ePHR for self-management. Overall, respondents on average noted that they were in agreement with the statements regarding their interest in intending to adopt an ePHR. Specifically, on a 7-point scale, responses to the adoption intention questions received an average score of 5.30 / 7.00, indicating that people with Type 2 Diabetes are very receptive to adopting an ePHR for self-management. This is consistent with a prior PHR research summary from Archer et al. (2011) which found that certain themes emerged from a synthesis of PHR/ePHR research, including the conclusions that people with chronic conditions tend to have the most interest in PHR/ePHRs, that one of the compelling reasons found to adopt an ePHR was the presence of a serious chronic illness, and that people with chronic conditions are more likely to adopt PHR/ePHRs.

In summary this research addresses a gap in the literature by examining ePHR adoption through a research model which is based on established theory from multiple relevant research streams. In order to understand the adoption of a health information technology, research should draw on theory from both the health care and technology fields of study. By doing so, this research was able to enrich the understanding of the motivations behind ePHR adoption.

7.1.1 Research Objective 1: PMT/OPMT Influence

To investigate and understand the influence of protection motivation theory (PMT) behavioural factors on the adoption of ePHRs by chronic disease patients.

Related Hypotheses – Adaptive Response Variables:

H1 – A higher level of response efficacy (RE) will positively influence ePHR Adoption Intention for chronic disease self-management.

H2 – A higher level of self-efficacy (SE) will positively influence ePHR Adoption Intention for chronic disease self-management.

H4 – A higher level of response costs (RC) will negatively influence ePHR Adoption Intention for chronic disease self-management.

It was hypothesized that participants would be more likely to intend to adopt an ePHR (i.e., ADOPT) if they had stronger beliefs that an ePHR would lead to better self-management (i.e., RE) and/or they were more confident in their abilities to use an ePHR (i.e., SE) and/or they felt the costs of adopting and using an ePHR were lower (i.e., RC). This current research supported each of these hypotheses (i.e., H1, H2, H4), with path coefficients of 0.457 ($p < .001$) for RE→ADOPT, 0.160 ($p < .01$) for SE→ADOPT and -.140 ($p < .01$) for RC→ADOPT. The Protection Motivation adaptive response variables behaved as expected, each having significant relations with behavioural intention (i.e., ADOPT), and in each case, the correct direction of the hypothesized relationship (i.e., positive for SE and RE, negative for RC). The relationships between SE→ADOPT (i.e., H2) and RC→ADOPT (i.e., H4) each produced a small effect size. However, the relationship between RE→ADOPT (i.e., H1) produced a medium effect size, thus indicating that while the adaptive response variables all have an impact on ePHR adoption intention, the largest effect comes from a person's belief that the ePHR will help them in their self-management of their Type 2 Diabetes. The findings of this research confirm earlier PMT research, most notably PMT meta-analyses (Floyd, et al., 2000; Milne, et al., 2000) which indicate that the adaptive response variables have effects on behavioural intentions. However, this research produced smaller effects than the meta-analyses reported for the relations between SE→ADOPT and RC→ADOPT. The effect size for RE→ADOPT was consistent with the two meta-analyses. The results for RE→ADOPT are very promising, as they indicate that respondents were able to see and understand the benefits of ePHRs for the self-management of their Type 2 Diabetes after only receiving information about this topic, and not actually having used an ePHR. This understanding in turn appears to lead to a greater likelihood of adopting an ePHR. Arguably this relationship may have been even stronger if respondents had been able to actually use, and see for themselves the benefits of an ePHR and how it could assist them in the self-management of their Type 2

Diabetes. This factor may also have been the reason why the effects observed for SE→ADOPT and RC→ADOPT may have been lower than earlier meta-analyses. Without the ability to actually use an ePHR, respondents may not have fully understood their potential abilities to use an ePHR and the cost/benefit trade-off in using an ePHR. The results of this study also indicate that compared to PMT studies in other contexts, the importance of self-efficacy (i.e., a person's belief in their abilities to use an ePHR) and response costs (i.e., their perception of the costs) are not as significant factors as response efficacy (i.e., what the ePHR can do for the individual) in the context of ePHR adoption intention.

Again, the findings of this current research are consistent with PMT meta-analyses (Floyd, et al., 2000; Milne, et al., 2000), which found significant relationships between each of these variables (i.e., RE, SE, RC) and intentions in a multitude of different contexts (i.e., health related, information systems, etc.) This research has found that these relationships are significant in the context of ePHR adoption by people with Type 2 Diabetes for the purposes of self-management, an area which had not previously been studied using PMT/OPMT. In addition, the responses to the open ended questions in this current research supported the quantitative findings. With regards to the response efficacy, or beliefs that an ePHR would lead to better self-management and positive health outcomes, respondents noted some of the following reasons why they would adopt an ePHR:

- *"It would give me a record of how my disease progresses and is controlled that I could refer to anytime I needed to. It would help my doctor know better what I do to help myself. It would give me greater confidence in my and my doctor's control over my disease."*
- *"To get [my Type 2 Diabetes] under control. To keep [my Type 2 Diabetes] under control. For better health."*
- *"I like using electronics for monitoring. I think this is the future. It would help me stay healthy."*
- *"Help me accomplish self-management of Type 2 Diabetes. Improve my performance in self-managing my Type 2 Diabetes. Make it easier to manage my Type 2 Diabetes."*

With respect to response costs, many of the responses to the open ended question regarding reasons why the participant would not adopt an ePHR had to do with the perceived costs. Forty-nine of the respondents specifically noted the word "cost" in their response to this open-ended question (note that potential monetary costs were not discussed in the ePHR video clips so as to not influence the responses), with comments such as:

- *"The cost of the product is the only real negative"*
- *"Cost is the only reason or barrier I see to using an ePHR."*
- *"Probably could not afford the cost."*
- *"Cost would be an important factor."*

Other respondents cited other potential 'costs' with comments such as:

- *"Too much time spent maintaining records. Like New Year resolutions, good intentions but wouldn't last long."*
- *"Too time consuming to enter all the data required to make the system useful."*

Related Hypotheses – Threat Variables:

H6a – A higher level of SEV will positively influence PTTF.

H6b – A higher level of SEV will positively influence SE.

H6c – A higher level of SEV will positively influence RE.

H7a – A higher level of VUL will positively influence PTTF.

H7b – A higher level of VUL will positively influence SE.

H7c – A higher level of VUL will positively influence RE.

It was hypothesized that the severity variable would positively affect the adaptive response (i.e., RE and SE) and PTTF variables (i.e., H6a, H6b, H6c). It was posited that increased feelings of severity regarding one's Type 2 Diabetes would positively influence a person's beliefs about ePHRs, specifically the more concerned a person was about the immediate impacts of their Type 2 Diabetes, the more likely they would believe in the benefits of using an ePHR for self-management, the stronger the fit between an ePHR and the task of Type 2 Diabetes self-management, and the more capable they would be in using an

ePHR. In essence, the greater their immediate concerns were regarding their Type 2 Diabetes, the more they would want to believe in the benefits and use of an ePHR. The results of this research support the hypotheses that higher levels of severity were positively related to feelings that the ePHR technology fit the task of self-management (i.e., H6a, SEV→PTTF), with a path coefficient of .267 ($p < .01$), and that higher levels of severity were positively related to a person's belief that ePHR technology could lead to better Type 2 Diabetes self-management (i.e., H6c, SEV→RE), with a path coefficient of .224 ($p < .05$). These two factors combined show that when a person's feelings of severity regarding their Type 2 Diabetes are higher, their beliefs that an ePHR is a good tool for Type 2 Diabetes self-management are also higher. With respect to the hypothesized relationship between people's feelings of severity and their belief in their ability to use an ePHR for Type 2 Diabetes self-management (i.e., H6b, SEV→SE), the results of this research indicate that there is not a significant relationship (with a path coefficient of only 0.13), and that increased feelings of severity do not enhance feelings of self-efficacy regarding using an ePHR. One reason for this finding may be the fact that the concept of severity is an immediate one (in that a person is assessing their concerns about the current effects of their Type 2 Diabetes) and the concept of self-efficacy is also in many ways immediate (in that the person is assessing whether or not they feel they can use an ePHR at the present time). This is in direct contrast to response efficacy, which can be considered more of a future factor in that the benefits of using an ePHR will accrue over time. This way of thinking is supported by the literature, with Compeau et al. (2006) reporting that Specific Computer Self-Efficacy (SCSE), which is the operationalization of Computer Self-Efficacy in a specific context (i.e., in this current research an ePHR) is different than General Computer Self-Efficacy (GCSE), in that SCSE judgements "are more susceptible to change, and are more important to understanding immediate [emphasis added] task performance" (p. 229). Therefore, respondents who reported higher levels of severity may have been thinking that they need to act immediately to do something regarding their Type 2 Diabetes, and did not feel they had time to learn the ePHR technology, thus reporting lower

levels of self-efficacy regarding the ePHR. However, they still believed in the longer term potential (i.e., response efficacy) of ePHR as a response to the health threat facing them.

In addition to the noted influences that severity has on the PMT adaptive response variables (i.e., RE and SE) as well as PTTF, the analysis of the indirect effects of severity on the intention to adopt an ePHR indicate that severity has a significant positive indirect effect (i.e., 0.155; $p < .05$) on ePHR adoption intention, fully mediated by PTTF, RE and SE. Thus, the results of this research suggest that elevated perceived levels of severity are indirectly related to a greater likelihood of ePHR adoption intention. This staged process of thinking that is part of the OPMT model indicates that higher feelings of severity coupled with an overall belief in the ePHR technology can positively influence ePHR adoption.

Similar to the hypotheses put forth for severity, it was hypothesized that the vulnerability variable would positively affect the adaptive response (i.e., RE and SE) and PTTF variables (i.e., H7a, H7b, H7c). It was posited that increased feelings of vulnerability regarding future complications arising from one's Type 2 Diabetes would positively influence a person's beliefs about ePHRs. Specifically, the more concerned people were about their future susceptibility to Type 2 Diabetes complications, the more likely they would believe in the benefits of using an ePHR for self-management, the stronger the fit between an ePHR and the task of Type 2 Diabetes self-management, and the more capable they would feel in using an ePHR. For the concept of vulnerability, in essence the greater future concerns were regarding complications from their Type 2 Diabetes, the more they would want to believe in the benefits and use of an ePHR. The results of this research support the hypotheses that higher levels of vulnerability were positively related to feelings that the ePHR technology fit the task of self-management (i.e., H7a, VUL→PTTF), with a path coefficient of .252 ($p < .01$), that higher levels of vulnerability were positively related to a person's belief that the ePHR technology could lead to better Type 2 Diabetes self-management (i.e., H7c, VUL→RE), with a path coefficient of .402 ($p < .001$) and their belief in their ability to use an ePHR for Type 2 Diabetes self-management (i.e., H7b, SEV→SE), with a path coefficient of .269 ($p < .01$). These results are logical, as the concept of vulnerability is a future one, in

that it is susceptibility to future complications rather than the severity of the immediate consequences of the disease. The relationship between vulnerability and response efficacy is stronger than the relationship between severity and response efficacy, as response efficacy is also a future related concept, in that the effects of better Type 2 Diabetes self-management through the use of an ePHR will materialize in both the short and long term. In addition, it is logical to expect the relationship between vulnerability and self-efficacy to be significant and positive, as people who are concerned about their vulnerability to the future complications of their Type 2 Diabetes also realize that they would have time to learn how to use an ePHR (and therefore they would report higher levels of SE), which can assist them to mitigate those future complications

In addition to the influences that vulnerability has on the PMT adaptive response variables (i.e., RE and SE) as well as PTTF, the analysis of the indirect effects of vulnerability on the intention to adopt an ePHR indicated that vulnerability has a significant positive indirect effect (i.e., 0.255; $p < .01$) on ePHR adoption intention. Similar to the discussion above regarding the relationship severity has with ePHR adoption intention, the relationship of VUL→ADOPT is fully mediated by PTTF, RE and SE. The results of this research suggest that elevated levels of perceived vulnerability are indirectly related to a greater likelihood of ePHR adoption intention. Again, similar to severity, this staged process of thinking that is part of the OPMT model indicates that higher feelings of vulnerability coupled with an overall belief in the ePHR technology can positively influence ePHR adoption. In fact, the indirect relationship of VUL→ADOPT is stronger than the indirect relationship from SEV→ADOPT, indicating that feelings of vulnerability to future complications are more important than immediate feelings of severity with respect to the decision to adopt an ePHR for Type 2 Diabetes self-management.

Summary of PMT/OPMT Influence

Overall, the influence that the PMT/OPMT variables have on intention to adopt an ePHR are very strong. Eight of the nine proposed hypotheses involving PMT were supported in this research. The threat variables (i.e., SEV and VUL) have significant direct positive relationships (except SEV→SE) with the

adaptive response variables (i.e., RE and SE) as well as significant indirect positive relationships with ePHR adoption intention. The adaptive response variables have significant direct positive relationships with ePHR adoption intention (except RC→ADOPT, which is significant and negative). An analysis of the research model which included only the PMT/OPMT variables (i.e., PAM and PTTF removed from the model) indicates a large amount of variance explained (i.e., $R^2 = 0.674$). These results were consistent with earlier research, confirming that PMT/OPMT has proven capabilities to explain behaviours in situations involving threats and coping responses, such as this research. Specifically, the results confirm the applicability of PMT/OPMT in understanding the motivations behind the adoption of an ePHR for self-management.

7.1.2 Research Objective 2: TTF and PAM Perspectives

To understand how the fit between chronic disease self-management task requirements, ePHR technology functionalities and individual characteristics influence the adoption of ePHRs through the lens of Task Technology Fit (TTF) and Patient Activation Measure (PAM).

Related Hypotheses:

H3 – A higher level of Perceived Task Technology Fit (PTTF) will positively influence ePHR Adoption Intention for chronic disease self-management.

H5a – A higher level of PAM will positively influence PTTF.

H5b – A higher level of PAM will positively influence SE.

It was hypothesized that the stronger the perceived fit that participants sensed between the task of Type 2 Diabetes self-management and the ePHR technology, the more likely they would be to intend to adopt an ePHR (i.e., H3). Findings from this research support this hypothesis, with a path coefficient between PTTF→ADOPT of 0.189 ($p < .05$). The relationship between these variables revealed only a small effect size, as another variable (i.e., RE) has more influence on ADOPT than PTTF has. However, the significant path relationship clearly supports the role that PTTF has in positively influencing an individual's intention to adopt an ePHR for self-management. This finding is in line with previous PTTF research, indicating the positive influence that PTTF has on subsequent intention behaviours (Lin &

Huang, 2008). Confirmation of this hypothesis is interesting, as it appears simply that the perception of the fit between the task and technology positively influences intention to adopt. This would somewhat indicate that if the target population's perception of fit can be influenced, there is a greater likelihood of ePHR adoption and subsequent use, as previous research supports the positive relationship between intention to adopt and actual usage (Davis & Venkatesh, 1996). Most TTF research involves participant assessment of the fit between the task and the technology after the participant has actually used the technology (e.g., Dishaw & Strong, 1998; Goodhue, et al., 2000; Klopping & McKinney, 2004). The fact that participants were able to formulate a positive relationship between perceptions of the fit between the ePHR and the task of self-management and the intention to adopt an ePHR, based on a video clip and prior to actual use, is a positive step in understanding how to potentially encourage more widespread ePHR adoption.

It was hypothesized that people who were more ready for the self-management of their chronic disease (i.e., higher levels of PAM) would be more likely to believe that the ePHR technology fit the task of Type 2 Diabetes self-management (i.e., H5a) and have a stronger belief in their capabilities to use an ePHR (i.e., H5b). Based on the findings regarding PAM, both of these hypotheses were supported, with path coefficients of 0.153 ($p < .05$) for PAM→PTTF and 0.188 ($p < .01$) for PAM→SE. The effect sizes for each of these relationships are small, with other variables having stronger relationships with PTTF (i.e., SEV→PTTF and VUL→PTTF) and with SE (i.e., VUL→SE). However, the significant path coefficients indicate that readiness for self-management of chronic disease plays an important direct role in perceptions of how well people feel an ePHR fits the task of Type 2 Diabetes self-management, their perceived ability to use an ePHR, and indirectly their intention to adopt an ePHR for self-management. This finding is interesting for a number of reasons. First, it suggests that a person's perception of the fit of a technology and the task is not solely influenced by the technology and the task but also by an individual's characteristics. In this research, the individual characteristic of the person's self-assessed readiness for the task influences the perception of fit. Second, and perhaps even more interesting, is the

finding that a person's readiness for self-management influences the perception of their ability to use a technology for self-management. While this positive relationship was hypothesized (i.e., H5b), it was considered exploratory as the relationship between PAM→SE had not been empirically examined before. This result is very compelling, as it shows that individual characteristics not traditionally associated with the perceived ability to use a technology do indeed have an impact. Finally, the significant and positive indirect relationship (0.059, $p < .05$) between PAM→ADOPT indicates that people who are more ready for the self-management of their chronic disease may be more likely to adopt an ePHR for self-management. This intriguing finding suggests that increasing a person's readiness for self-management may be one way to improve ePHR adoption. Previous PAM research has found that it is possible to increase one's PAM score through educational interventions (Hibbard, et al., 2007), in essence increasing their readiness for self-management, which could in-turn lead to ePHR adoption and use.

Summary of PTTF and PAM Influences

The results of this research study suggest that the TTF and PAM variables play a significant role either directly or indirectly in the intention to adopt ePHR technology by chronic disease patients. The significant relationship between PTTF→ADOPT indicates that the fit between the task and the technology is an important factor in the intention to adopt an ePHR. In addition, the significant relationship discussed earlier between SE→ADOPT is also important to reiterate here. It is logical to interpret the SE construct as a representation for the fit between the individual and the technology (i.e., people who perceive their abilities to use the technology as high would likely see a strong fit between themselves and the technology). Therefore the significant relationship between SE→ADOPT supports the notion of the importance of the fit between the technology and the individual. Finally, the indirect positive relationship between PAM→ADOPT, along with the significant positive direct relationships between PAM→PTTF and PAM→SE supports the belief that the fit between the task and the individual (represented by PAM in this current research) is important in the intention to adopt an ePHR. In summary, the relationships between the task requirements (self-management of Type 2 Diabetes),

technology (ePHR) and individuals (Type 2 Diabetes patients) along with their direct and indirect relationships with intention to adopt an ePHR support the FITT concept put forth by Ammenwerth et al. (2006) in that the fit between all of these elements is important in addressing the adoption of an Information Technology.

7.1.3 Research Objective 3: Role of Educational Interventions

To understand the role Diabetes Complication (DC) and ePHR educational interventions have on various constructs in the research model.

Related Hypotheses:

H8a – Individuals receiving intense DC education will experience higher perceptions of Severity (SEV) compared to individuals receiving no DC education.

H8b – Individuals receiving intense DC education will experience higher perceptions of Vulnerability (VUL) compared to individuals receiving no DC education.

H9a – Individuals receiving advanced ePHR education will experience higher perceptions of Response Efficacy (RE) compared to individuals receiving basic ePHR education.

H9b – Individuals receiving advanced ePHR education will experience higher perceptions of Self-Efficacy (SE) compared to individuals receiving basic ePHR education.

H9c – Individuals receiving advanced ePHR education will experience higher perceptions of Perceived Task-Technology Fit (PTTF) compared to individuals receiving basic ePHR education.

This research included two different educational interventions designed to manipulate participants responses for specific PMT and PTTF variables. A total of five hypotheses were developed, under the belief that the individuals receiving the intense education regarding Type 2 Diabetes complications (as compared to the group that received no Diabetes complication education) would feel higher levels of severity (i.e., H8a) and feel higher levels of vulnerability (i.e., H8b). In addition, those who received advanced ePHR education (compared to those who received basic ePHR education) would feel that the ePHR technology would lead to better Type 2 Diabetes self-management (i.e., H9a), experience higher perceptions of their ability to use an ePHR (i.e., H9b) and believe that there was a better fit between the ePHR and the task of Type 2 Diabetes self-management (i.e., H9c).

Manipulation checks designed to determine if the participants were indeed manipulated by the educational intervention videos clearly show that both of the manipulations were understood by the participants. Specifically, significant differences in the responses to the manipulation check questions were found between the groups receiving intense DC education and the control group that received no DC education, with respect to their perception that the video increased their concern about the health threats posed by their Type 2 Diabetes (i.e., the group receiving intense education reported that the video made them more concerned). In addition, there were significant differences in the responses to the manipulation check questions between the groups receiving basic versus advanced ePHR education. Specifically, the group receiving advanced ePHR education reported that the video increased their understanding of both the benefits from, and how to use an ePHR for Type 2 Diabetes self-management, as well as increased their confidence level in potentially using an ePHR for Type 2 Diabetes self-management, as compared to the group receiving basic ePHR education. Therefore, the video clip educational interventions used in this research provided the intended manipulations.

Diabetes Complication Educational Intervention Effects

The DC educational intervention results indicate that the SEV and VUL variables were not affected as hypothesised (i.e., H8a, H8b). The results of the analysis regarding the effects of DC education on SEV showed no significant differences between the mean responses for the SEV variable between the group receiving intense DC education and the group receiving no DC education (i.e., mean of 4.980 versus 5.157, $F = 1.728$, $p = 0.190$). Similar to this result, the analysis of the effects of DC education on VUL also showed no significant differences between the mean responses for the VUL variable between the group receiving intense DC education and the group receiving no DC education (i.e., mean of 5.321 versus 5.415, $F = 0.428$, $p = 0.513$).

Why Didn't Fear Appeals Work?

Given the successful manipulation check results, it was therefore perplexing that the DC educational intervention, which in essence was a fear appeal, failed to affect the specific PMT variables that it was

designed to manipulate. Perhaps even more unexpected was the fact that the group receiving no DC education actually experienced slightly higher perceptions of SEV and VUL compared to the group receiving intense DC education (although not significant). Therefore, an examination of the literature as well as responses to applicable open ended questions was undertaken to try to understand this unexpected result. This undertaking led to the following possible explanations for this finding:

a) **The DC educational intervention content was not fear-provoking enough and/or did not provide any new information:** It is quite conceivable that the content of the intense video, while containing alarming statistics and graphic images was simply not effective in eliciting a sufficient sense of fear/threat regarding the health effects of Type 2 Diabetes. This is supported by responses to open-ended questions provided by respondents, who in some cases indicated the video clip had little to no effect on them. The following feedback was provided by respondents (who viewed the intense DC education video clip) to the question "What effects did the Diabetes [complication] information that was presented to you in the first video clip have on your decision regarding whether or not you would adopt and use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes?"

   - *"I am already reasonably familiar with the information in the video clip."*
   - *"I knew it all so no effect."*
   - *"No effect, I know the consequence of type II Diabetes if it isn't controlled."*
   - *"Not much. Already had concerns about Diabetes."*
   - *"Was aware of these problems from family experience so it had little impact for me."*
   - *"Very little. When first diagnosed with Type 2 Diabetes I went through an information training session arranged by my doctor that covered all aspects of the disease."*

   In addition, the alarming statistics provided may not have been trusted by participants, as some respondents noted:

   - *"I found the statistics were like yellow journalism and somewhat misleading".*
   - *"Interesting video but [I] am not convinced."*

Previous PMT research has also experienced difficulties in manipulating the threat variables. Courneya and Hellsten (2001) in a study intended to manipulate the threat/fear of skin cancer noted "Our failure to manipulate PV [Perceived Vulnerability] is perplexing and does not allow us to comment on its potential role in cancer prevention and exercise motivation ... The mean of both groups was about 3.0 on the seven-point PV scale, indicating that the failure likely resulted from an ineffective high PV condition ... Clearly, instilling perceptions of vulnerability to cancer in young people is a major challenge for cancer prevention practitioners." (Courneya & Hellsten, 2001, p. 63)

b) **People with Diabetes are already concerned:** The elevated scores of both groups who received differing levels of DC education indicate that on average people with Diabetes are already concerned about the immediate and future health effects of their chronic disease. The mean responses for SEV and VUL were 5.072 and 5.370 respectively. These results indicate that, on average all participants were a full point or higher above the midpoint (i.e., four) on the 7-point Likert scale that assessed SEV and VUL, regardless of whether they viewed the intense DC education video or not. Mainstream publications support this conclusion, with statements such as:

- *"After Diabetes diagnosis, many type 1 and Type 2 diabetics worry about their life expectancy." (diabetes.co.uk - the global diabetes community)*
- *"In my practice as a Diabetes educator, some people are almost paralyzed by the fear of developing Diabetes complications." (Davidson & Moreland, 2010)*
- *"Even if you're the healthiest of diabetics, you're probably still worried about the long-term complications of the metabolic disease."(Wride, 2013)*

c) **Fear appeals do not always work:** There is prior research that has examined why fear appeals work, and why they do not. Witte and Allen (2000) state "Although considerable laboratory research has shown that fear appeals (persuasive messages that arouse fear) motivate behavior change across a variety of behaviors, public health researchers and practitioners continue to contend that fear appeals backfire." (p. 591). Earlier work by Witte stated that the empirical findings regarding fear appeals were inconsistent and contradictory (Witte, 1992), with a number of authors demonstrating their

ineffectiveness (Janis & Feshbach, 1953; Kohn, et al., 1982). One reason suggested for why fear appeals may not work lies in the intensity of the message. Some research suggests that a minimum level of fear/threat is required for the message to have an effect (Shen, 2011). However, excessive fear can lead to a number of reactions that may hinder message reception, such as message avoidance, selective memory and message rejection (Shen, 2011). It is quite plausible that the graphic content and alarming statistics involved in the intense DC education may have had the opposite impact on some participants to what was intended, and in fact the attempt to stimulate fear may have instead hindered the reception of the information.

The preceding discussion of the findings indicates that the fear appeal manipulation via the intense DC education video did work, but the manipulation did not result in elevated perceptions of severity and vulnerability. A number of possible reasons were provided in the discussion above, but it is not possible to determine exactly why severity and vulnerability were not affected as hypothesized.

ePHR Educational Intervention

While the results of the Diabetes complication educational intervention were not as hypothesised, the ePHR educational intervention results indicate that the PMT and PTTF variables they were designed to manipulate were in fact manipulated. Specifically, the results of the analysis regarding the manipulation effects of the ePHR education on the self-efficacy (SE) variable show that the group receiving advanced ePHR education reported significantly higher perceptions of their abilities to use an ePHR (i.e., mean of 5.310 versus 5.056, $F = 4.363$, $p < .05$). The results of this analysis indicate that it is possible to manipulate an individual's perceptions of their ability to use an ePHR by providing them with more advanced information/education that demonstrates how to use an ePHR for self-management.

The results of the analysis regarding the manipulation effects of the ePHR education on the perceived task-technology fit (PTTF) variable indicate that the group receiving advanced ePHR education reported significantly higher perceptions that the ePHR technology was a good fit for the task of Type 2 Diabetes self-management (i.e., mean of 5.452 versus 5.140, $F = 7.187$, $p < .001$). The results of the

ePHR educational interventions reveal that the perception of fit between an ePHR and the task of self-management can be manipulated by providing advanced education regarding the use and benefits of an ePHR.

Finally, the results of the analysis involving the effects of the ePHR educational intervention on the response efficacy (RE) variable were somewhat inconclusive. The ANOVA analysis revealed that the difference in mean responses for the RE variable (between the group receiving the differing levels of ePHR education) is not significant at the $p < .05$ level, but is marginally significant at the $p < .10$ level (significance level of .072). While this result is not as statistically significant as the others (see Section 6.4.4 for an explanation of marginal significance) it appears that the group receiving advanced ePHR education formulated higher perceptions that the ePHR technology would lead to better Type 2 Diabetes self-management. This result indicates that the perception of the benefits of an ePHR for self-management may be manipulated through ePHR education.

Summary of Educational Intervention Influences

The results of the DC educational intervention suggest that the fear appeal did not have the intended effect on respondent's perceptions of severity and vulnerability to Type 2 Diabetes complications. In fact, somewhat of the opposite effect occurred, whereby people receiving intense DC education reported lower perception of severity and vulnerability. A number of reasons were suggested for this finding, and it is possible that either the video was too intense, leading to the fear appeals message not being correctly received, or that people with Type 2 Diabetes are already concerned, and therefore the fear appeal was unable to increase these feelings. Overall, the results of the analysis pertaining to the ePHR educational intervention indicate that this intervention produced the expected outcomes for the most part. Individuals who are provided with more advanced education regarding the ePHR technology are more likely to see the fit between an ePHR and the task of Type 2 Diabetes self-management, and be more likely to believe in their abilities to use an ePHR for Type 2 Diabetes self-management. There were somewhat inconclusive results for response efficacy with the ANOVA analysis result close to being significant,

indicating that advanced ePHR education may have a positive impact on an individual's perception that the ePHR technology could lead to better Type 2 Diabetes self-management.

7.1.4 Research Objective 4: Effects of Individual Factors

To study the effects individual factors (e.g., demographic, socio-economic, health condition, etc.) have on various constructs in the research model.

There were no hypotheses developed for the effects that individual factors would have on the variables in the research model, as this objective is considered exploratory. However, the findings detailed in Section 6.4.5 reveal that a number of individual factors have an effect on the variables in the research model.

By far the individual factor with the most significant impact on the variables in the model was age, and in all cases, increases in age resulted in decreases in the perceptions of certain variables in the model. All completed analyses showed that as the age of the respondent increased, the feelings of severity and vulnerability decreased, the belief that the ePHR technology fit the task decreased, the perceived ability to use an ePHR decreased and the belief that the ePHR would lead to better self-management decreased. These results are consistent with earlier research which found significant negative relationships between age and severity (Plotnikoff & Higginbotham, 1998), age and vulnerability (Plotnikoff & Higginbotham, 2002), age and self-efficacy (Plotnikoff, et al., 2009a) and age and response efficacy (Plotnikoff, et al., 2009a; Plotnikoff, et al., 2009b; Rudman, et al., 1999). In addition, two of the three applicable analyses (i.e., ANOVA and correlation but not PLS - see Table 52) also indicated that as the age of the respondent increased, the likelihood of the respondent intending to adopt an ePHR decreased. However, this last finding regarding age and ePHR adoption intention should be viewed with some caution, as one of the three analyses (i.e., PLS) did not support the finding, and prior research revealed no relationship between age and intention to create (i.e., adopt) an ePHR (Whetstone & Goldsmith, 2009). The results regarding the impact of age on the various elements in the model are somewhat disconcerting, as older people are one of the groups noted for the potential to achieve greater benefits on average from ePHRs.

Unfortunately, prior research has shown that age related increases in chronic disease and a lack of technology efficacy are potential barriers to the adoption of ePHRs technology amongst the elderly population (Archer, et al., 2012).

The level of control respondents felt they have over their Type 2 Diabetes also significantly affected a number of variables in the model. Specifically, the greater control respondents felt that they have over their Type 2 Diabetes was found to be related to a decrease in their feelings of severity and vulnerability regarding their disease, but was also related to an increase in their readiness for self-management (i.e., PAM). While there is no known specific prior research that investigated the relationship between Type 2 Diabetes control and feelings of severity and vulnerability, our findings are consistent with 'real-life' experiences regarding these concepts. The United States Centres for Disease Control and Prevention (2012) reports that people involved in Chronic Disease Self-Management programs demonstrated significant improvements in their ability to manage their condition (similar to control over their chronic condition) which was in turn related to less worrying about their health (similar to severity and vulnerability feelings). The relationship with PAM is consistent with earlier research, which notes that "activation reflects the degree to which one feels 'in charge' of one's own health." (Hibbard & Cunningham, 2008, p. 4). For people with Type 2 Diabetes, being in charge of one's own health would involve achieving a greater level of control over their Type 2 Diabetes. People with Type 2 Diabetes would most likely lead more contented lives if their feelings of severity and vulnerability were reduced. Helping people with Type 2 Diabetes to gain more control over their chronic disease could be accomplished through the adoption and use of an ePHR, which in turn could lead to the reduction in feelings of severity and vulnerability.

The level of respondent self-reported knowledge regarding their general health significantly affected a number of variables. The general health knowledge control variable is very similar to the health literacy concept, which can be defined as the understanding of basic health information required to make health related decisions (Greene, et al., 2005). Similar to the findings regarding level of control over a person's Type 2 Diabetes, a higher level of general health knowledge was negatively related to feelings of severity

and vulnerability. While there is no known prior research detailing the relationship between general health knowledge/health literacy and the threat variables, there is logic in the findings from this current research. Arguably, when people understand more information about health in general, they would have a better understanding of the potential threats from their condition, and through this understanding, individuals may experience a reduction in their level of concern regarding their chronic disease. Additionally, this research showed that higher levels of general health knowledge were positively associated with readiness for self-management. This is consistent with prior research which found a significant positive relationship between patient activation (i.e., PAM) and health literacy levels (Greene, et al., 2005). Therefore, improving the health literacy levels amongst people with Type 2 Diabetes could be a path to both reduce their anxiety regarding their chronic condition, and a way to increase intention to adopt an ePHR for self-management, as health literacy has been shown to improve a person's readiness for self-management (Greene, et al., 2005).

The results of this research indicate that the PAM variable was most affected by individual factors. Specifically, this research study indicates that PAM is positively associated with education, income, knowledge of Type 2 Diabetes, individual control over Type 2 Diabetes (as discussed previously), general health condition and general health knowledge (as discussed previously). These findings are consistent with previous PAM literature, with earlier studies finding that people who are "more educated and have higher incomes tend to be more activated [i.e., higher PAM scores]" (Hibbard & Cunningham, 2008, p. 3) and those with better perceived health status (i.e., similar to better general health condition) scored higher on the PAM scale (Hibbard & Cunningham, 2008). The finding regarding the positive relationship between knowledge of Type 2 Diabetes and PAM is consistent with prior literature. As mentioned above, previous research has demonstrated a significant positive relationship between PAM and health literacy levels. People with higher health literacy levels would most likely have greater knowledge about their chronic condition, and this current research has demonstrated that these individuals would then show a greater readiness for self-management. Interestingly in this current research the age factor which was significantly associated with numerous variables in the model, had no impact on PAM. This is not

consistent with earlier PAM literature, which found that younger people tend to have higher PAM scores (Hibbard & Cunningham, 2008). This last result is encouraging, as it suggests that older people with Type 2 Diabetes are just as ready for self-management as younger people with Type 2 Diabetes. Given that PAM is positively related to PTTF, SE and indirectly to intention to adopt an ePHR, an objective therefore should be to determine a way to transform this self-management readiness into self-management action, potentially through ePHR usage.

While it is interesting to examine individual factors which had an impact on variables in the model, it is also interesting to examine those individual demographic factors which appear to have no impacts on any variables in the model. From all of the individual factors captured in this research study, gender was the only control variable that had no significant impacts on any of the variables in the model. This is in line with previous research which found no impact of gender on the PMT variables (i.e., SEV, VUL, RE and SE) (Graham, et al., 2006) or fit (i.e., TTF) (Lee, et al., 2007) or intention to create (i.e., adopt) an ePHR (Whetstone & Goldsmith, 2009). This finding would suggest that both men and women with Type 2 Diabetes exhibit similar feelings of severity and vulnerability, that they have similar feelings regarding their ability to use an ePHR, similar feelings regarding the belief that an ePHR could lead to better self-management, similar views that the ePHR technology fits the task of self-management, and similar perceptions of the costs of using an ePHR. This finding suggests that men and women are similar regarding their intentions to adopt an ePHR for self-management, indicating that both genders are just as likely to use an ePHR.

7.2 Contributions

Findings generated from this research study provide significant theoretical, practical and societal contributions which are detailed below.

7.2.1 Contributions to Theory

This research makes a number of academic contributions in the area of theory and Consumer Health Information Technology research. First, from an academic standpoint this research validates the earlier findings of Tanner Jr. et al. (1991) and Ordered Protection Motivation Theory, in that the ordering of the PMT variables (with threat preceding efficacy variables) is a worthwhile and useful variation of the traditional PMT model. Researchers considering the use of PMT in their research should examine the potential for OPMT to be more applicable to their research model. The OPMT model was developed over 20 years ago, yet a limited number of research studies have employed this potentially advantageous variation of the PMT model. Confirmation of the value of OPMT through research such as this study can serve to encourage other researchers to use OPMT. This may be especially important when the conceptual link between the threat and the proposed intended adaptive behaviour may not be obvious, and therefore the effect of the threat is more likely to be mediated by the efficacy of the potential response. For example, in PMT studies that examine smoking cessation, the link between the health threats of smoking and the potentially positive behaviour of quitting smoking (i.e., intended behaviour) are relatively straightforward and understandable. However, in a study such as this research, where the link between the health threats from Type 2 Diabetes and the use of an ePHR are not so clear and obvious, an ordered way of thinking may be more likely to occur (i.e., the threat from my Type 2 Diabetes is high $\rightarrow$ an ePHR can help $\rightarrow$ I will adopt an ePHR).

Secondly, to the best of my knowledge this is the first known study to combine PMT/OPMT with TTF. In fact, an examination of the PMT/OPMT literature reveals only a handful of studies that attempted to incorporate other theories into the research (e.g., Herath & Rao, 2009b; Ifinedo, 2012). In essence, this current research examined phenomena of interest through the combination of different lenses (i.e., PMT/OPMT and TTF). A recent Editor's Comment in the Academy of Management Journal (Okhuysen & Bonardi, 2011) stresses the difficulties and importance of combining different theoretical lenses to further the understanding of a phenomena of interest, stating "We have a formidable opportunity

in front of us to contribute to our field by taking down walls and building bridges between perspectives. Many great theoretical developments and many new explanations for unexplained phenomena could follow, and therefore management scholars are urged to take up this challenge. Combining multiple theoretical lenses to develop new explanations of management phenomena and solve managerial challenges will continue to be a critical aspect of how research is conducted in our field. However, authors must also make special efforts in their attempts to combine theoretical lenses" (Okhuysen & Bonardi, 2011, pp. 10-11). This current research combines theoretical lenses from two different streams (i.e., health care and IS), while at the same time ensuring this was done with careful consideration to the phenomena being investigated. Specifically, this research combined PMT/OPMT (due to its focus on health care and the ability to introduce educational interventions) with PTTF (due to the task orientation of self-management of Type 2 Diabetes using an ePHR technology). In addition, this current research answers a call made to incorporate IS theory into Consumer Health Information Technology adoption studies (Or & Karsh, 2009), selecting PTTF as the IS theory due to its task-based focus.

Third, to the best of my knowledge this is the first known study to incorporate PAM in a theoretical model and to subsequently study that model with more advanced statistical methods (i.e., SEM). Prior PAM research has typically investigated PAM in isolation or in combination with basic demographic or health related variables, and has taken either a qualitative only approach (Dixon, et al., 2009) or used first generation statistical methods such as correlation, simple regression, etc. (Greene & Hibbard, 2012; Greene, et al., 2005; Hibbard, et al., 2009; Hibbard, et al., 2007; Lorig, et al., 2010; Lorig, et al., 2009; Rask, et al., 2009; Remmers, et al., 2009) when investigating PAM. This current research contributes by not only validating the usefulness of PAM as a measure, but also as an important component in a more sophisticated research model, with validated significant relationships between PAM and IS/PMT theoretical concepts and constructs (i.e., TTF and SE). Going forward, PAM should therefore be considered as a potential variable to be included in Consumer Health Information Technology studies where self-management is part of the context of the study.

Fourth, to the best of my knowledge this is the first known empirical study of ePHR adoption that utilizes either PMT or TTF as the theoretical foundation for the research model. In fact, previous ePHR adoption and usage studies for the most part do not employ theoretical foundations for the research, but rather examine ePHR adoption via qualitative, observational or descriptive methods. Those ePHR adoption studies that use theoretical foundations mostly use TAM or TAM related theory such as UTAUT and TPB. Given that self-management of one's health often involves complex and time-consuming tasks, this current research provides unique contributions by examining the phenomena of interest through PTTF and through theory developed in the health care field (i.e., PMT/OPMT). In addition, other technology studies typically look at the adoption of IS in a universal manner, assuming people use IS in a similar way. This current study is unique in that it looked at the adoption of a technology (i.e., an ePHR) for a specific purpose, namely the task of Type 2 Diabetes self-management, rather than examining the adoption of an ePHR from a general perspective.

Fifth, the incorporation of educational interventions in this paper has interesting contributions to academics. The DC educational intervention results indicate that highly intense fear appeals may not function as intended, and may in fact induce the opposite effect in research participants. Researchers employing fear appeals with respect to chronic and other diseases may wish to 'tone down' the message in order to produce the desired effect. Unfortunately, the results of this research simply add fuel to the fire in the debate between the effectiveness (or ineffectiveness) of fear appeals in research. For the ePHR educational intervention, the successful manipulation of the PMT and PTTF variables indicates that advanced demonstration based education of new and innovative technologies (such as ePHRs) can be useful in encouraging new ways of thinking and ultimately behavioural changes (i.e., adoption and use). The results of this current research further the educational intervention research work completed by scholars such as Venkatesh et al. (2002), Mun and Davis (2003), Venkatesh and Bala (2008) and Soucek and Moser (2010) by examining the relationships between demonstration/training interventions and both the PMT and TTF constructs. In addition, the results of this research were consistent with earlier research

(Davis, et al., 1989) in confirming the use of video clips as an effective way to demonstrate in a realistic way a prototype of an emerging technology.

Finally, while the context of this research is the adoption of ePHRs by people with Type 2 Diabetes, the findings from this study are, in all likelihood, generalizable to the larger chronic disease population, which accounts for approximately 37% of the entire United States population (DeVol & Bedroussian, 2007) as well as the population of people who are pre-diabetic (approximately 35% of the United States population according to the United States Department of Health and Human Services National Diabetes Information Clearinghouse (2011), and also to the segments of the population who are at risk for Type 2 Diabetes (for example, people considered clinically obese, which accounts for approximately 34% of the United States population according to Shields, et al., 2011). Therefore, the results of this survey are generalizable to over one-third of the North American population, or approximatley 90+ million people. However, the generalizability of these findings to these other populations needs to be proven via future research.

7.2.2 Contributions to Practice and Society

From an ePHR system developer/provider perspective, this study is valuable in that it demonstrates that the most important factors in increasing ePHR adoption involve ensuring prospective users are fully informed of the short and longer term benefits of using an ePHR, that they are made to feel comfortable that they can use an ePHR, that they can see the fit between the ePHR technology and the task of self-management, and that they believe the costs of using an ePHR are offset by the potential benefits. This last element indicates that it may not be the actual cost of ePHR usage that is important, but rather that the perceived benefits outweigh these costs, meaning that ePHR systems could be priced based on an assessment of the potential costs (i.e., monetary, time, effort) versus benefits calculation. In addition, given the indirect relationship between readiness for self-management (i.e., PAM) and ePHR adoption, ePHR system developers can either focus on targeting those people who are more ready for self-management, or focus efforts on increasing self-management readiness in the target population.

This study also revealed important findings in that positively focused demonstration/training on the benefits and usage of ePHRs is much more likely to lead to ePHR adoption than negatively focused fear appeals that discuss the potential health issues that may arise when chronic conditions are not managed properly. This is important to ePHR system developers/providers in that simply providing advanced ePHR education via video clip demonstrations (on both the expected benefits and how to use an ePHR) may be one of the required elements that can lead to greater ePHR adoption.

Finally, from a demographic standpoint, this study determined that ePHR system developers will need to further research the age effect, attempting to understand different ways to attract older users to adopt and use ePHRs. For the most part, this study revealed that as people age, the likelihood of ePHR adoption diminishes. However, further research that specifically focuses on ePHR adoption motivational factors amongst the elderly population could allow ePHR system developers/providers to target this market segment. This is especially crucial with the combination of the increasing proportion of the population that is aging, the incidence of chronic conditions amongst the elderly and the fact that the elderly population are one of the groups that can achieve strong benefits from ePHR usage.

For physicians, strategies that improve chronic disease patient self-management are beneficial in improvements to the health of their patients, more effective patient-physician encounters (due to the availability of self-monitoring data) and a reduction in the time demands chronic patients place on physicians. These improvements in self-management could be brought about by greater ePHR adoption (accompanied by the appropriate use of ePHR functionalities that help chronic disease patients monitor their disease, populate the ePHR with actual data, and physician support for patients in the self-management of their disease via ePHRs). The results of this research suggest that people with chronic conditions, and specifically those who report higher levels of activation (i.e., on the PAM scale) are more likely to adopt and use an ePHR. By understanding this motivator for adoption, physicians can target patients who fit this characteristic and tailor their specific ePHR educational information to increase adoption rates. One good place to start may involve physicians assessing their patient's readiness for self-management through the use of the Patient Activation Measure. Physicians can then make optimal use of

their time in working with patients who are ready for self-management, encouraging them to adopt a tool such as an ePHR for self-management, rather than trying to work with those patients who are not yet ready for self-management and therefore have a lower likelihood of adopting an ePHR. In addition, the findings regarding educational interventions suggest that in order to improve ePHR adoption, physicians should focus efforts on helping their patients understand the benefits of self-managing their chronic condition with an electronic tool such as an ePHR, rather than focusing on the negative consequences of not managing their chronic disease, as fear appeals did not appear to have an effect on the target audience.

From a societal standpoint, studies which determine how to increase the adoption of ePHRs are of benefit. It has been shown that chronic care patients can benefit through improving disease self-management. Given ePHRs can assist them in improving self-management, this study can potentially help chronic disease sufferers via improving their health condition, life expectancy, etc. Governments and health care organizations around the world are discussing the benefits of ePHRs and how they can assist patients and potentially reduce some of the economic burden of chronic disease health care, which by one estimate in the United States totalled $1.3 trillion in 2003 (DeVol & Bedroussian, 2007). By better understanding ePHR adoption, especially among chronic care patients, this study can potentially aid society in encouraging greater adoption and usage of ePHRs, and potentially reducing some of the direct (e.g., treatment) and indirect (e.g., lost productivity) impact costs associated with chronic disease. A recent study estimates that the net annual cost savings of integrated ePHR usage in the United States could be $19 billion (Kaelber, et al., 2008). Given the strained financial situation of health care systems around the world, improving ePHR adoption could produce needed substantial financial benefits. Improved patient self-management through ePHRs could potentially reduce patient/subscriber costs for Health Management Organizations (HMO's) and government health agencies, and these cost savings could potentially be passed back to subscribers, employers or tax payers, or perhaps reinvested in the health care system.

7.3 Limitations

As with most academic research studies, there are some limitations to this research which should be noted. First, with respect to participants, only people with Type 2 Diabetes that had access to a computer and the Internet were involved in this research. This is due to the fact that the survey was completed online via a survey website. Thus it is logical to assume participants had experience in using a computer and the Internet, and therefore the results may not be generalizable to the entire population of people with Type 2 Diabetes. In addition, given that the adoption and usage rate of the Internet are lower for older adults (Zickuhr & Madden, 2012), the results of this research may not be generalizable to all elderly people, specifically those older adults who may not use computers or the Internet. However, given this research focused on examining the adoption of an electronic PHR (ePHR), focusing on those people with computer and Internet experience makes logical sense, as the ePHR described or demonstrated to the participants was an Internet/computer based application.

Second, given the focus of this research was on people with Type 2 Diabetes, it remains to be determined if the results of this research will be applicable to people with other chronic diseases which may not involve a similar set of complex and time consuming tasks in the self-management of the chronic disease (e.g., asthma). Further research using these other groups as participants is therefore recommended.

Third, given the online survey involved self-reporting and that this was the sole source of measurement for the data analysis, it is possible that common method bias (CMB) may exist. However, two different statistical analyses ruled out the existence of CMB, and therefore the likelihood of CMB is low.

Fourth, with respect to the survey logistics, although precautions were taken to ensure participants watched the videos in their entirety, because the survey was completed anonymously off-site there are no guarantees they actually watched all of the video material. Participants could have involved themselves in other activities (e.g., moved away from the computer, looked at other web pages, etc.) while the video

was playing. However, respondents were asked to ensure they watched the videos completely, and given that respondents were told that the videos were important, and that this research could potentially benefit people with Type 2 Diabetes, it is expected that they took the instructions seriously and focused their attention on the videos.

Fifth, from a data perspective, some minor data issues were noted previously, specifically with respect to the fact that for some constructs the data was not normally distributed. Previous literature has shown that the statistical method used for this current research (i.e., Partial Least Squares) is relatively robust to deviations from normality (Chin, 1998), and that with larger sample sizes (i.e., >200) like this current research included, deviations from normality are not a serious issue (Hair, et al., 2010b). In addition, the survey data collection process involved a cross sectional design, where all data were collected from the sample population at a specific point in time. While this method is relatively common in academic research, it is limited in that: i) there is no evidence of time-based relationships between the variables; ii) it is difficult to infer appropriateness of causal relationships; and, iii) alternative explanations for the findings may not be appropriately ruled out (Carlson & Morrison, 2009). Therefore, future research may involve a longitudinal approach, where intention to adopt and potentially actual use of an ePHR (when ePHRs are more common) could be examined.

Sixth, from a construct operationalization and data analysis perspective, this is the first known time PAM has been incorporated in a SEM model. The measurement of PAM is via a validated 13-item scale that is then converted into a single-item measure. While single-item measures are fully supported via the partial least squares method of data analysis (Ringle, et al., 2012), researchers often prefer multiple-item measures. However, to remain consistent with the recommended calculation process for PAM (Insignia Health LLC, 2011) a single-item measure was necessary. It should be reiterated that this single item composite score was calculated from the validated 13-item PAM scale, and therefore this single item should be highly reliable.

A final limitation of this current research study is due to the focus on North American (i.e., Canadian and United States) culture and their specific healthcare systems. Over 99.5% of respondents to this

survey were from North America. Given both the cultural and health care system differences between North America and other parts of the world, results from this study may vary in other parts of the world. Therefore, the reproduction of this research in other parts of the world is recommended.

7.4 Future Research

The results of this research answered most of the research questions, and generally the hypotheses proposed were supported. However, as mentioned previously the results with respect to the Type 2 Diabetes complications educational intervention were perplexing and warrant further research. One of the research areas that directly relates to this puzzling result is the effects that the DC educational intervention has in the model. Specifically, this current research investigated whether or not the provision of intense, negative, threat provoking messaging has a relationship with people's feelings of severity, vulnerability and their perceptions regarding the use of ePHRs to help self-manage their Type 2 Diabetes. In layman's terms, the research intended to discover whether or not scaring specific segments of the population (i.e., people with Type 2 Diabetes) might change their feelings and behaviour. As discussed in the findings, one reason for the unexpected results may be the fact that the fear appeal was not strong enough for people who already have Type 2 Diabetes, and for the most part, may already have been aware of the negative effects regarding the complications of their disease. Similar to some expert thinking about graphic images on cigarettes, fear appeals may be successful in changing thinking for people who have just started to smoke, or who haven't started yet, but may be ineffective for people who are already smokers (Menon, 2011). Analogous to this, fear appeals may not be effective for people who already have Type 2 Diabetes, but may be effective for those people who are pre-diabetic, for people who may be at risk for Type 2 Diabetes (e.g., obesity, family history, etc.) or for the population in general.

Pre-Diabetes "is a condition in which individuals have blood glucose, also called blood sugar, or [H_bA1_C] levels higher than normal but not high enough to be classified as Diabetes. People with pre-Diabetes have an increased risk of developing Type 2 Diabetes, heart disease, and stroke." (U.S. Department of Health and Human Services National Diabetes Information Clearinghouse, 2011). The

United States Department of Health and Human Services has published data on the incidence of pre-Diabetes that is extremely alarming. The 2010 statistics show that in the United States, "35 percent of U.S. adults ages 20 years or older had pre-Diabetes – 50 percent of those aged 65 years or older. Applying this percentage to the entire United States population in 2010 yields an estimated 79 million Americans ages 20 years or older with pre-Diabetes" (U.S. Department of Health and Human Services National Diabetes Information Clearinghouse, 2011). This indicates that for every person in the United States with Diabetes, there are approximately three who are pre-diabetic. There is no reason to believe that these statistics would be significantly different in Canada. Studies show that people with pre-Diabetes who lose weight and increase their physical activity can prevent or delay Type 2 Diabetes and in some cases return their blood glucose levels to normal. Therefore it is logical to assume that the pre-diabetic population could benefit from the use of an ePHR to monitor weight, exercise and blood glucose levels amongst other elements in an effort to suppress or eliminate the risk of developing 'full-blown' Type 2 Diabetes. In addition, the greater size of this population would make research with pre-diabetics generalizable to a much larger portion of the population. Therefore, future research should test the current model and educational interventions with people diagnosed as pre-diabetic. In a similar line of thinking, the current research model and educational interventions could also be tested with specific portions of the population who exhibit the risk factors for Diabetes. It is estimated that 34.4% of the United States population (ages 20-79) are considered obese (Shields, et al., 2011), which translates into approximately 80 million people (Howden & Meyer, 2011; Shields, et al., 2011). Given that obesity is considered to be a risk factor for Type 2 Diabetes (Garg, et al., 2013), it would be logical to complete this research with a sample of people who are considered to be clinically obese. Securing participants for this study may be easier than securing people who are pre-diabetic, as people may not know they are pre-diabetic, but they may know if they are considered to be obese. In addition, the generalizability of this study would be very high, as a large proportion of the population is considered to be obese.

Given that respondents in this research were not able to actually use an ePHR, but rather viewed video clips that provided information and/or a demonstration of an ePHR, it would be interesting to

understand if and how the results of this research would be different if participants actually used an ePHR. Therefore, future research using a similar research model (i.e., intention to adopt would be replaced with actual use or continued intention to use) and following a similar research methodology is proposed. The results of this research would be interesting to examine, as participants would be able to provide responses based on actual ePHR usage. Longitudinal research where data is gathered both before using an ePHR and at different times after using an ePHR would allow for the understanding of how ePHR usage changes over time. In addition, this would allow for the inclusion and examination of attrition rates, which are common in eHealth studies (Eysenbach, 2005).

Based on the successful integration of health based theory (i.e., OPMT) and IS theory (i.e., TTF), future research should continue to examine different theories from these two disciplines to understand and test where there may be logical opportunities for theoretical integration. Of particular interest is Information Systems Continuance Theory (ISC) (Bhattacherjee, 2001), which could potentially be combined with different health based theory to understand the factors involved in the continued use of Consumer Health Information Technologies.

Finally, future research should also examine ePHR adoption amongst other cultures with other types of health care systems to determine the results for those countries, and also to compare those results to this current study of North American respondents. This research could reveal if factors such as culture or the specifics of the healthcare system play a role in the adoption or ePHRs.

7.5 Conclusion

The overarching objective of this research was to examine the motivational factors behind ePHR adoption through the combination of theory from both the health care and Information Systems (IS) streams. It is important that research involving Consumer Health Information Technologies considers theory from both health care and information systems, as the investigation pertains to a health technology. The examination of the motivational factors involved in ePHR adoption was completed in the context of individuals with Type 2 Diabetes adopting an ePHR for the task of chronic disease self-management.

Given that ePHR adoption is low, and people with chronic conditions are noted as one of the groups who can benefit the most from ePHR usage, improving ePHR adoption is an important undertaking. To achieve this important objective, this study combined Ordered Protection Motivation Theory (OPMT) with Task-Technology Fit (TTF) and Patient Activation Measure (PAM). OPMT is an excellent theory to understand behavioural intentions (such as adoption) in a health care context. TTF is an established IS theory that is well suited for examining the adoption of technology that is to be used for specific complex tasks. Finally, PAM provides an assessment of the fit between an individual and the task at hand, in this research, providing an understanding if the individual is ready for the task of self-management of their chronic condition.

The results of this study reveal that the combination of OPMT, TTF and PAM has excellent explanatory power and that for ePHR adoption intention, an ordered way of thinking (with threat followed by efficacy followed by adoption intention) is likely the process used by individuals. A secondary objective of this study was the examination of the effects that educational interventions had on the variables, and the intention to adopt an ePHR. The results for this objective revealed that fear appeals may not be effective in this context, but that provision of advanced technology education is an important part of the endeavour to improve ePHR adoption rates. Given the low ePHR adoption rates, much more research into the factors involved and the motivations behind the adoption of this technology is warranted.

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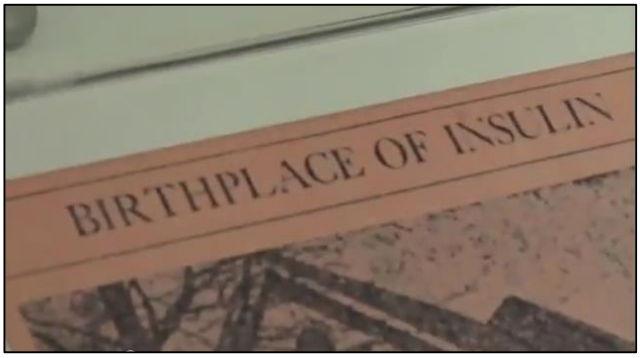
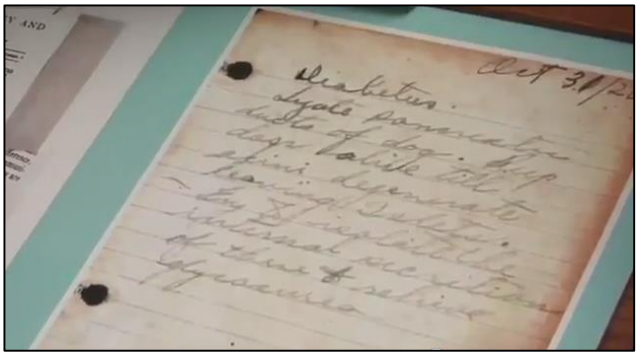
Appendix A – Video Clip Storyboards

Part 1: Diabetes Complications – None (i.e., DC=0)





Part 2: Diabetes Complications – Intense (i.e., DC=1)

DIABETES COMPLICATIONS

Type 2 Diabetes can lead to serious health complications or even death, as the following video outlines…

People with Type 2 Diabetes have **up to 4 times as many visits to doctors** compared to people without diabetes

When people with Type 2 Diabetes are hospitalized, they can expect to spend **up to 6 times as long in the hospital** compared to people without diabetes

Compared to the general population, people with Type 2 Diabetes are **3 times as likely** to develop **high blood pressure**, which can cause **serious health complications**

More than 1 in 4 people with Type 2 Diabetes develop **diabetic neuropathy** which leads to **blindness**

Type 2 Diabetes is the **leading cause** of new cases of adult **blindness**

Type 2 Diabetes is the leading cause of **kidney disease**, accounting for almost **half of all new cases**

Diabetes patient undergoing dialysis

People with Type 2 Diabetes are **hospitalized** with **chronic kidney disease 6 times more often** than those without diabetes

People with Type 2 Diabetes are **hospitalized** with **heart conditions up to 4 times as often** as those without diabetes

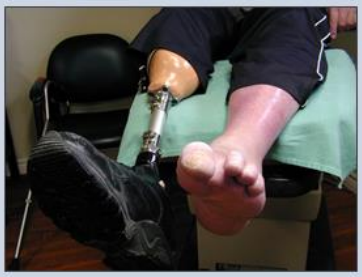
The risk of **stroke** and the serious complications associated with it is up to **4 times higher** among people with Type 2 Diabetes

Up to **70%** of people with Type 2 Diabetes have **nervous system damage** known as **neuropathy** which can lead to **ulcerations and amputations**

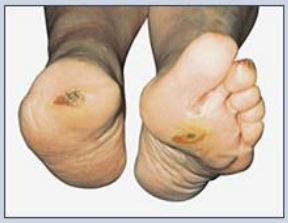
Sores on the foot of a person sufering from diabetic neuropathy

People with Type 2 Diabetes are **hospitalized** for **lower limb amputations 19 times more often** than those without diabetes

Over **60% of lower-limb amputations** occur in people with Type 2 Diabetes



1 out of every 10 people with Type 2 Diabetes may require a **lower limb amputation**

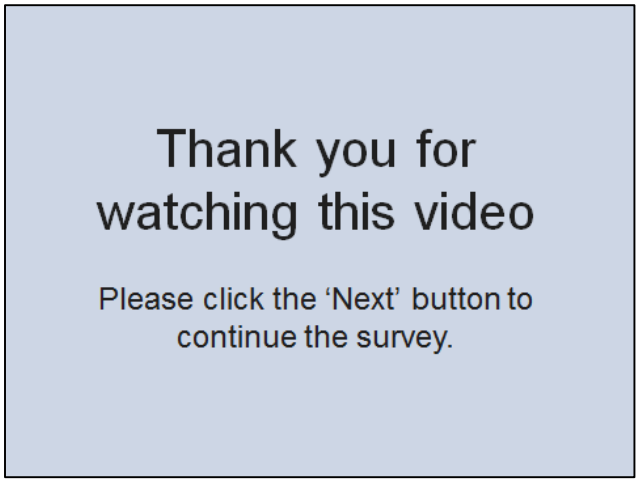


Over **80% of people** with Type 2 Diabetes will **die** as a result of **heart disease or stroke**

Type 2 Diabetes contributes to almost **250,000 deaths** per year in the USA.

Type 2 Diabetes is the **7th leading cause of death** in the USA.

Type 2 Diabetes can take as much as **10 years off of your life…**


Thank you for watching this video
Please click the 'Next' button to continue the survey.

Part 3: ePHR Education – Basic (i.e., ePHR=0)

An Electronic Personal Health Record (**ePHR**) is a technology that permits you to securely gather, store, manage and share your personal health information

ePHRs are personal – they are owned, managed and controlled by the patient

ePHRs can reside on a computer, on the Internet, or on a smartphone such as the iPhone

ePHRs often contain a diverse range of personal health-related information such as:

- *Personal profile details including emergency contacts and health insurance information*
- *A calendar system with health-related appointments and reminders*
- *Health record information such as medications, immunizations, allergies and lab test results*

ePHRs often contain a diverse range of personal health-related information such as:

- *A wellness tracking system for self-reported items such as blood pressure and exercise*
- *Alerts to indicate if your personal wellness tracking readings require further attention*
- *Personal health tips and medical news*

In addition to storing an individual's personal health information, **ePHRs** can provide value-added services such as:

- *Drug interaction checking*
- *Appointment scheduling*
- *Messaging system allowing you to email your doctor and share personal wellness tracking results*

Thank you for watching this video

Please click the 'Next' button to continue the survey.

Part 4: ePHR Education – Advanced (i.e., ePHR=1)

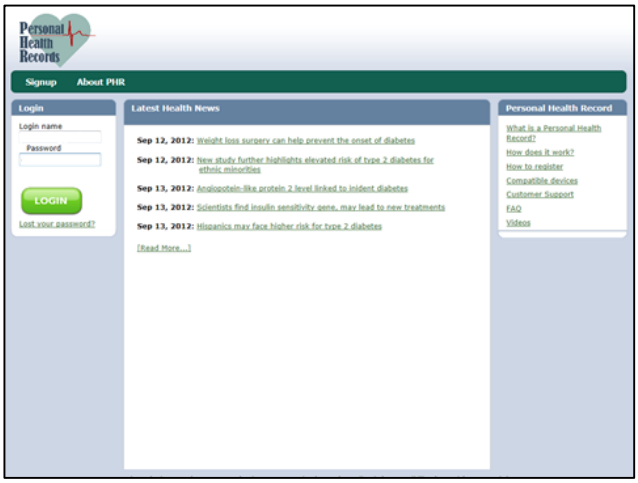
People with Type 2 Diabetes should track a number of items on a daily, weekly, monthly or quarterly basis:

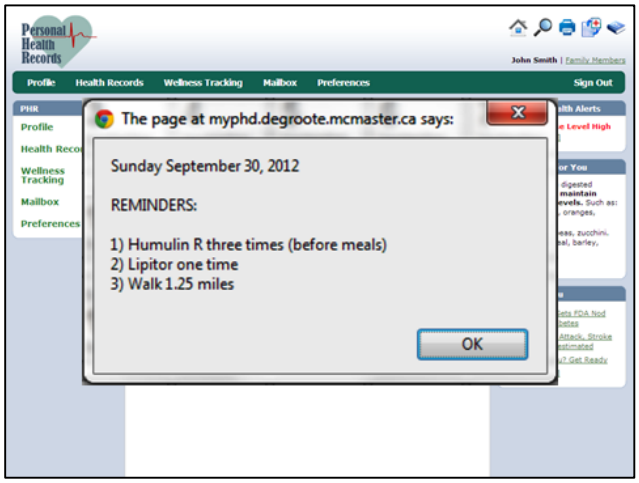
- *Blood Glucose*
- *Blood Pressure*
- *HbA1c*
- *Cholesterol*
- *Weight*
- *Food/Diet*
- *Medications*
- *Exercise*

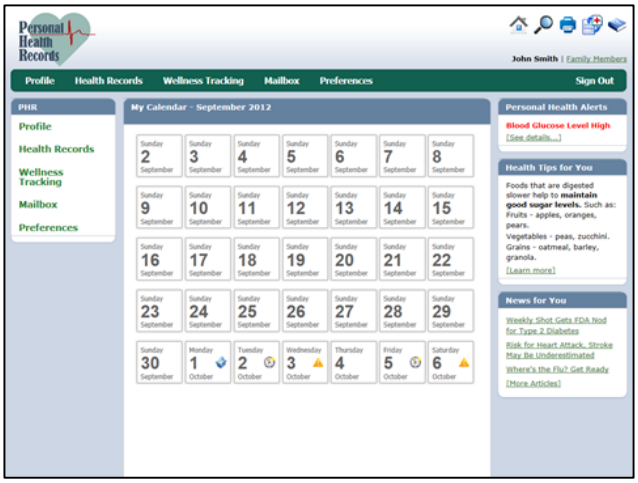
Studies show that people with Type 2 Diabetes that participate in the self-management of their chronic disease:

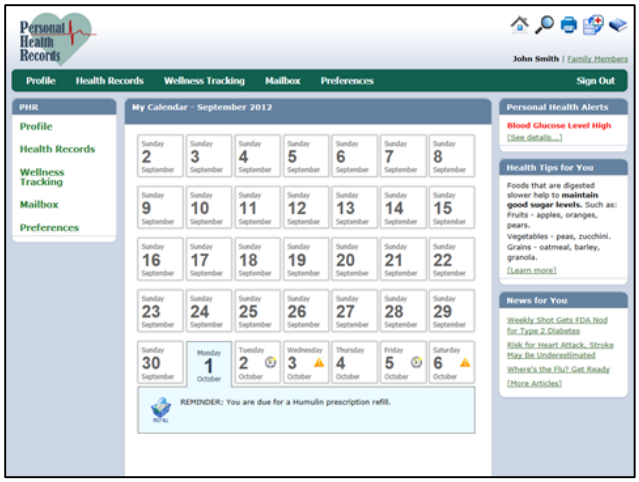
- *Reported improved overall health*
- *Had fewer hospitalizations and days spent in the hospital*
- *Had a reduction in emergency room and other hospital visits*
- *Achieved a reduction in both blood glucose and HbA1c levels*

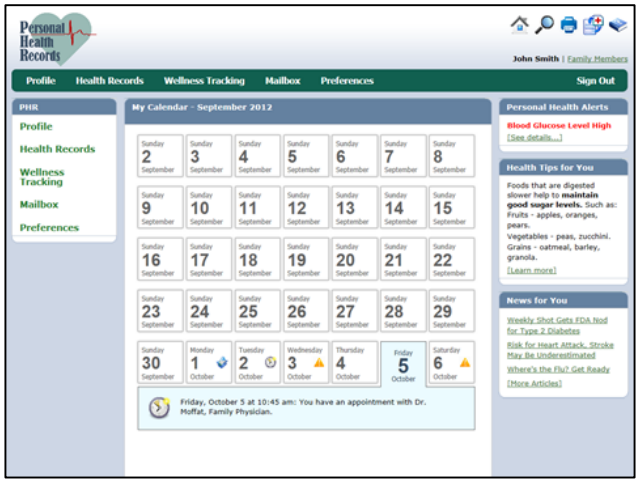
ePHRs can be used by people with chronic conditions such as Type 2 Diabetes in the self-management of their disease…








Personal Health Records
John Smith | Family Members
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
PHR
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
My Calendar - September 2012
REMINDER: You are due for a Humulin prescription refill.
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
Foods that are digested slower help to maintain good sugar levels. Such as:
Fruits - apples, oranges, pears.
Vegetables - peas, zucchini.
Grains - oatmeal, barley, granola.
[Learn more]
News for You
Weekly Shot Gets FDA Nod for Type 2 Diabetes
Risk for Heart Attack, Stroke May Be Underestimated
Where's the Flu? Get Ready
[More Articles]


Personal Health Records
John Smith | Family Members
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
PHR
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
My Calendar - September 2012
Friday, October 5 at 10:45 am: You have an appointment with Dr. Moffat, Family Physician.
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
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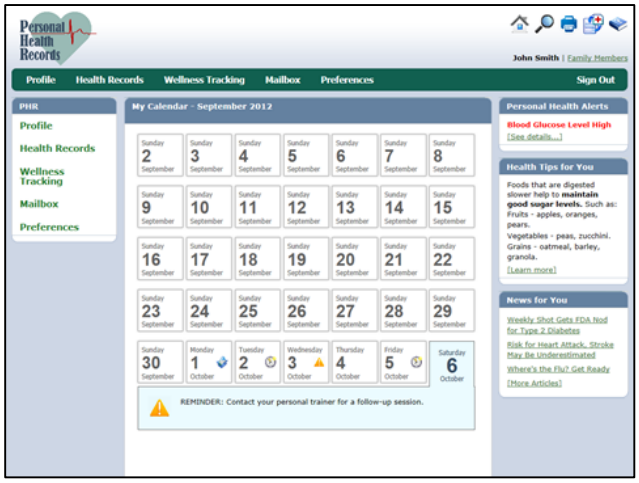
Personal Health Records
John Smith | Family Members
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
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Profile
Health Records
Wellness Tracking
Mailbox
Preferences
My Calendar - September 2012
REMINDER: Contact your personal trainer for a follow-up session.
Personal Health Alerts
Blood Glucose Level High
[See details...]
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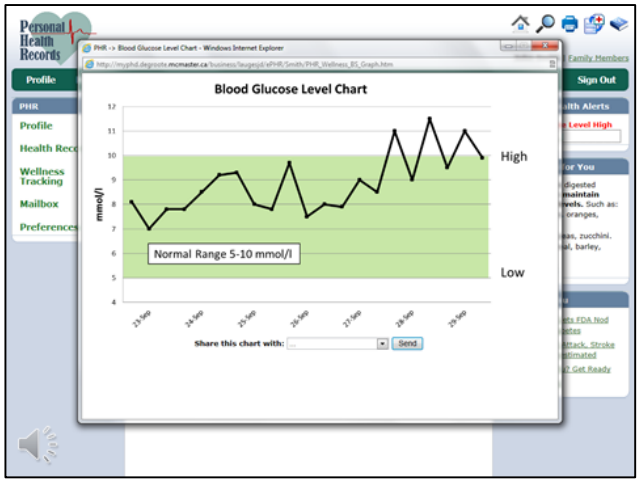
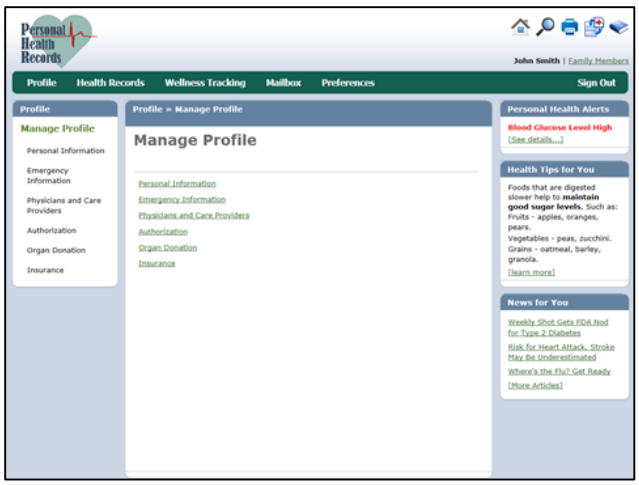

Personal Health Records
Blood Glucose Level Chart
mmol/l
High
Low
Normal Range 5-10 mmol/l
Share this chart with:
Send


Personal Health Records
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Profile
Manage Profile
Personal Information
Emergency Information
Physicians and Care Providers
Authorization
Organ Donation
Insurance
Profile » Manage Profile
Manage Profile
Personal Information
Emergency Information
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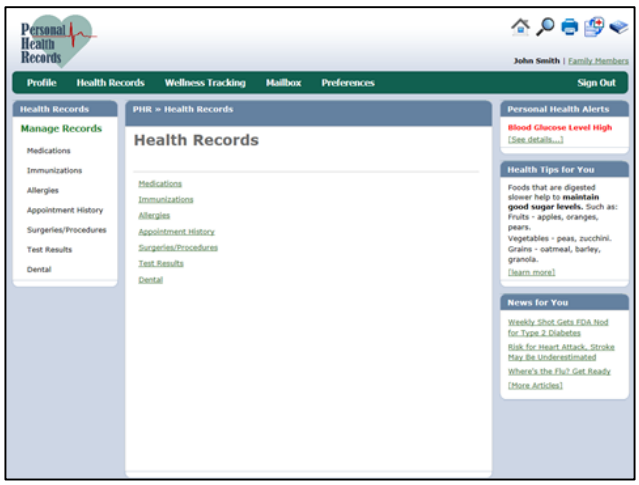
Personal Health Records
John Smith | Family Members
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Health Records
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Health Records
Manage Records
Medications
Immunizations
Allergies
Appointment History
Surgeries/Procedures
Test Results
Dental
PHR » Health Records
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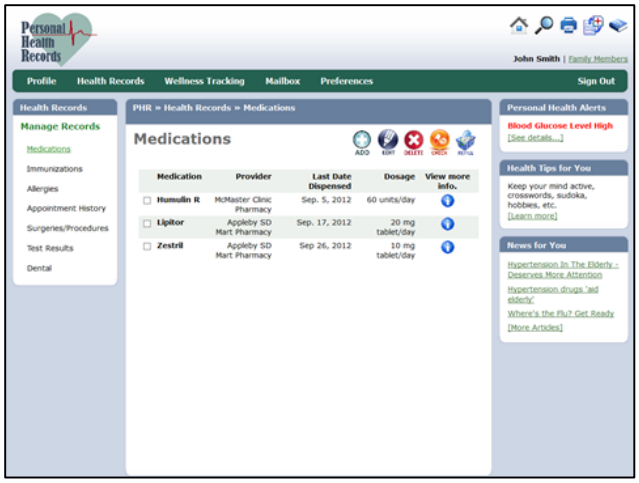
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Health Records
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Allergies
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Surgeries/Procedures
Test Results
Dental
PHR » Health Records » Medications
Medications
ADD
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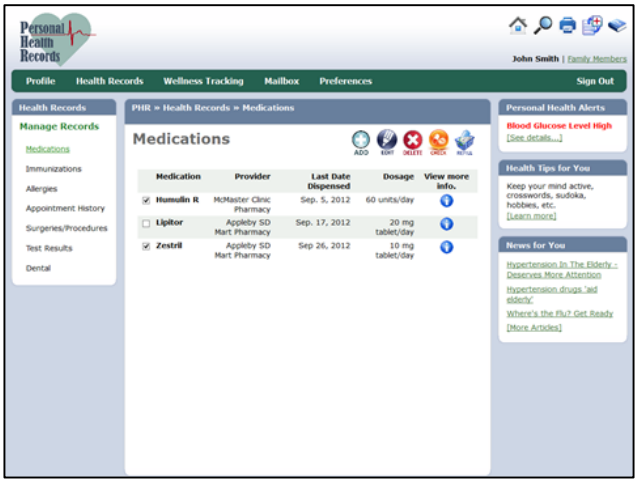
CHECK
REFILL
Medication
Provider
Last Date Dispensed
Dosage
View more info.
Humulin R
McMaster Clinic Pharmacy
Sep. 5, 2012
60 units/day
Lipitor
Appleby SD Mart Pharmacy
Sep. 17, 2012
20 mg tablet/day
Zestril
Appleby SD Mart Pharmacy
Sep 26, 2012
10 mg tablet/day
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
Keep your mind active, crosswords, sudoku, hobbies, etc.
[Learn more]
News for You
Hypertension In The Elderly - Deserves More Attention
Hypertension drugs 'aid elderly'
Where's the Flu? Get Ready
[More Articles]


Personal Health Records
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Wellness Tracking
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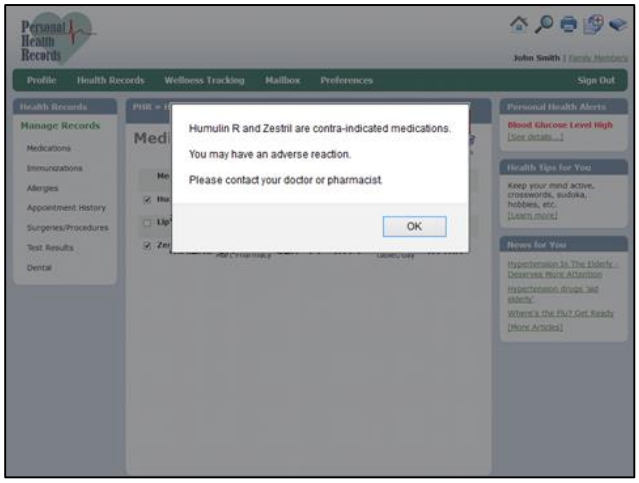
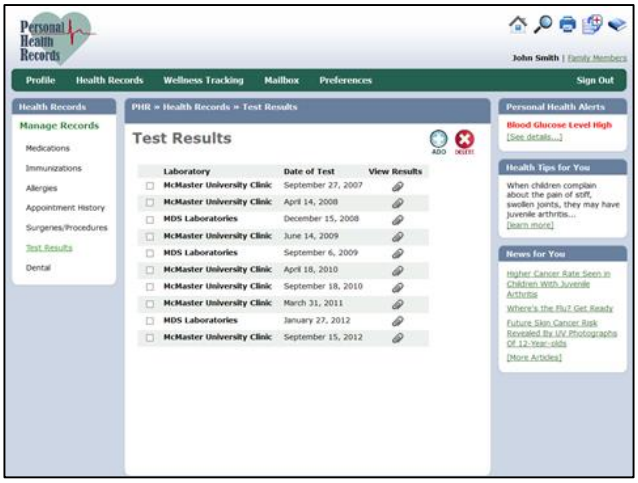

Humulin R and Zestril are contra-indicated medications.
You may have an adverse reaction.
Please contact your doctor or pharmacist.
OK


Personal Health Records
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Health Records
Wellness Tracking
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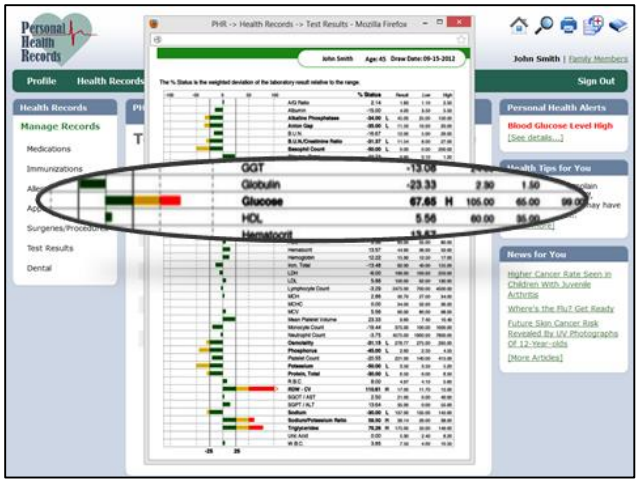
Sign Out
Health Records
Manage Records
Medications
Immunizations
Allergies
Appointment History
Surgeries/Procedures
Test Results
Dental
PHR » Health Records » Test Results
Test Results
ADD
DELETE
Laboratory
Date of Test
View Results
McMaster University Clinic
September 27, 2007
McMaster University Clinic
April 14, 2008
MDS Laboratories
December 15, 2008
McMaster University Clinic
June 14, 2009
MDS Laboratories
September 6, 2009
McMaster University Clinic
April 18, 2010
McMaster University Clinic
September 18, 2010
McMaster University Clinic
March 31, 2011
MDS Laboratories
January 27, 2012
McMaster University Clinic
September 15, 2012
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
When children complain about the pain of stiff, swollen joints, they may have juvenile arthritis...
[learn more]
News for You
Higher Cancer Rate Seen in Children With Juvenile Arthritis
Where's the Flu? Get Ready
Future Skin Cancer Risk Revealed By UV Photographs Of 12-Year-olds
[More Articles]


Personal Health Records
John Smith | Family Members
Profile
Health Records
Sign Out
Health Records
Manage Records
Medications
Immunizations
Surgeries/Procedures
Test Results
Dental
PHR -> Health Records -> Test Results - Mozilla Firefox
GGT
Globulin
-23.33
Glucose
67.65 H
105.00
65.00
HDL
5.56
60.00
Hematocrit
Personal Health Alerts
Blood Glucose Level High
[See details...]
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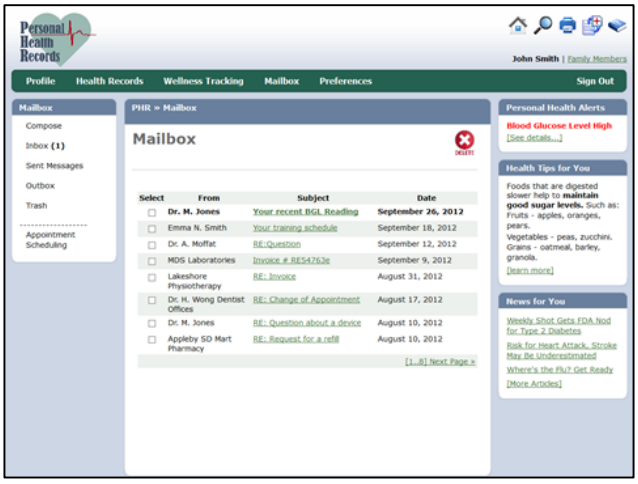
Personal Health Records
John Smith | Family Members
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
Mailbox
Compose
Inbox (1)
Sent Messages
Outbox
Trash
Appointment Scheduling
PHR » Mailbox
Mailbox
Select
From
Subject
Date
Dr. M. Jones
Your recent BGL Reading
September 26, 2012
Emma N. Smith
Your training schedule
September 18, 2012
Dr. A. Moffat
RE:Question
September 12, 2012
MDS Laboratories
Invoice # RES4763e
September 9, 2012
Lakeshore Physiotherapy
RE: Invoice
August 31, 2012
Dr. H. Wong Dentist Offices
RE: Change of Appointment
August 17, 2012
Dr. M. Jones
RE: Question about a device
August 10, 2012
Appleby SD Mart Pharmacy
RE: Request for a refill
August 10, 2012
[1..8] Next Page »
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
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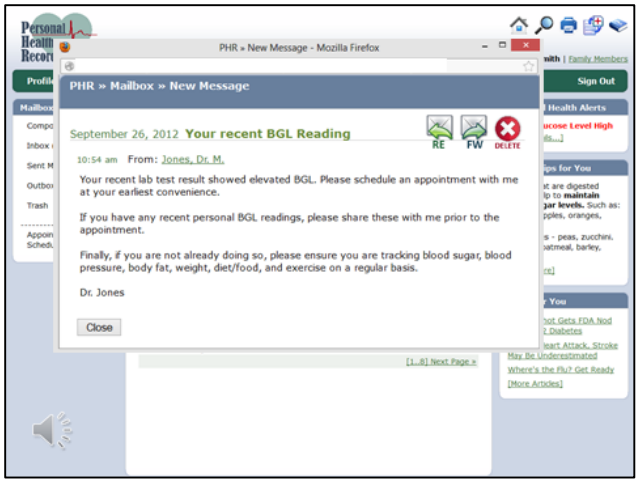
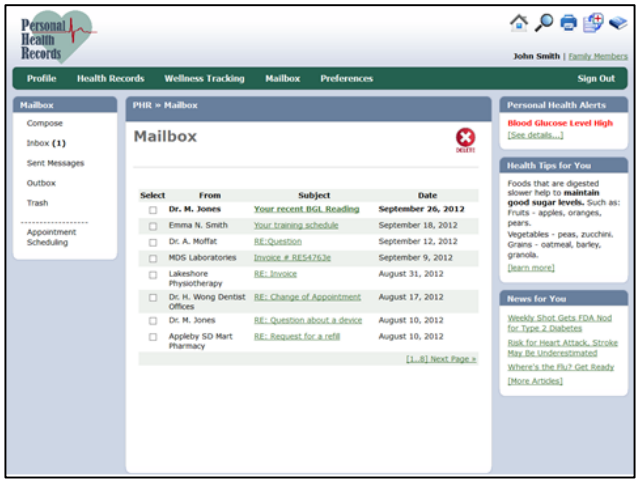

PHR » New Message - Mozilla Firefox
PHR » Mailbox » New Message
September 26, 2012 Your recent BGL Reading
RE
FW
DELETE
10:54 am From: Jones, Dr. M.
Your recent lab test result showed elevated BGL. Please schedule an appointment with me at your earliest convenience.
If you have any recent personal BGL readings, please share these with me prior to the appointment.
Finally, if you are not already doing so, please ensure you are tracking blood sugar, blood pressure, body fat, weight, diet/food, and exercise on a regular basis.
Dr. Jones
Close


Personal Health Records
John Smith | Family Members
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
Mailbox
Compose
Inbox (1)
Sent Messages
Outbox
Trash
Appointment Scheduling
PHR » Mailbox
Mailbox
Select
From
Subject
Date
Dr. M. Jones
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September 26, 2012
Emma N. Smith
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[See details...]
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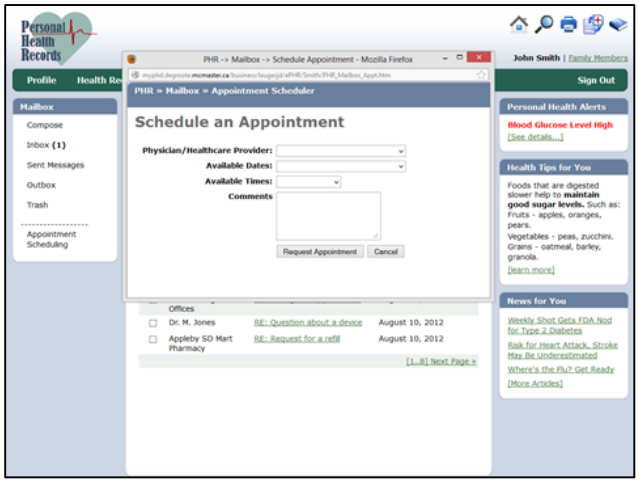
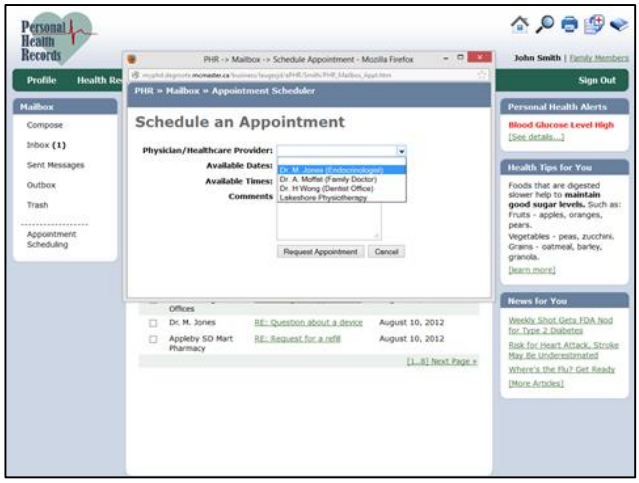
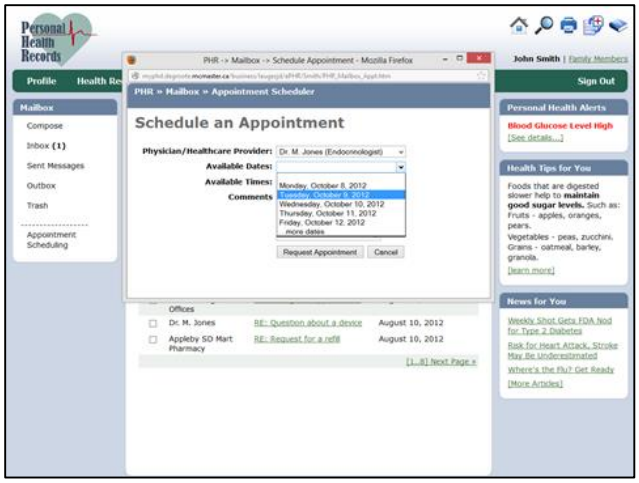
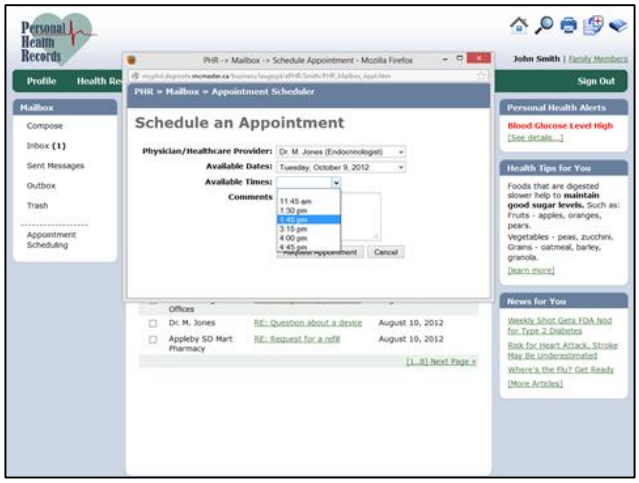
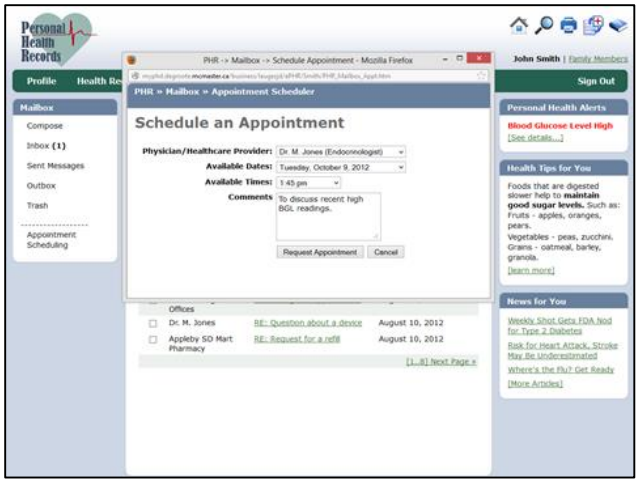
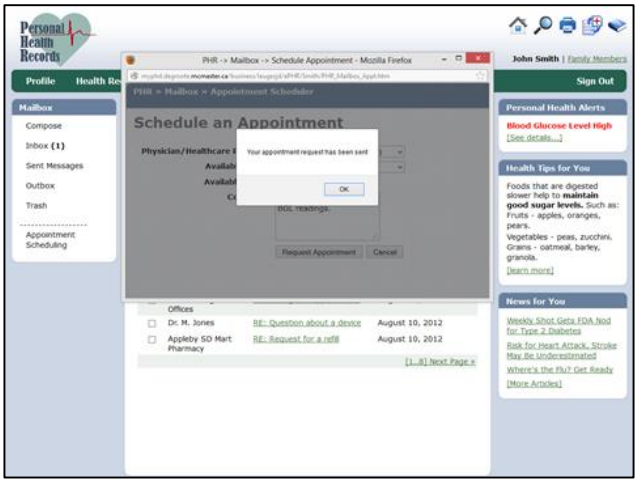

PHR -> Mailbox -> Schedule Appointment - Mozilla Firefox
PHR » Mailbox » Appointment Scheduler
Schedule an Appointment
Physician/Healthcare Provider:
Available Dates:
Available Times:
Comments
Request Appointment
Cancel

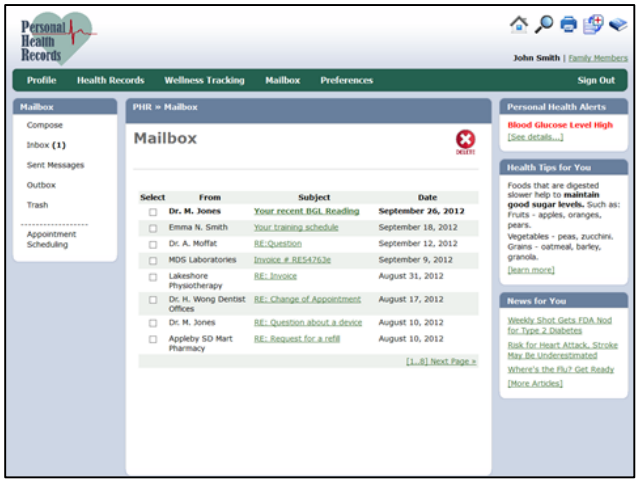

PHR -> Mailbox -> Schedule Appointment - Mozilla Firefox
PHR » Mailbox » Appointment Scheduler
Schedule an Appointment
Physician/Healthcare Provider:
Available Dates:
Available Times:
Comments
Dr. M. Jones (Endoonnologist)
Dr. A. Moffat (Family Doctor)
Dr. H'Wong (Dentist Office)
Lakeshore Physiotherapy
Request Appointment
Cancel

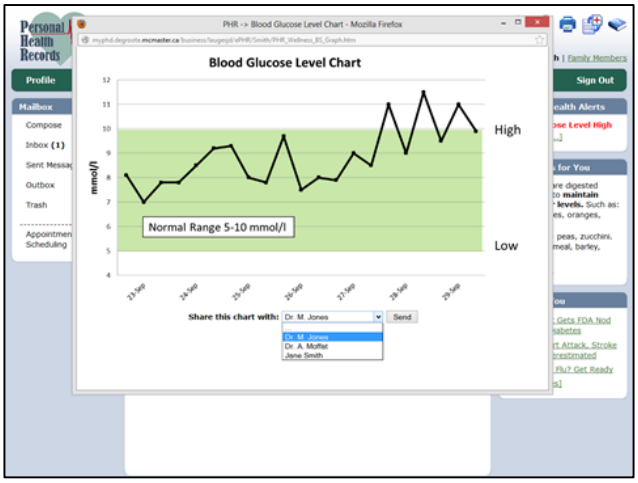

PHR -> Mailbox -> Schedule Appointment - Mozilla Firefox
PHR » Mailbox » Appointment Scheduler
Schedule an Appointment
Physician/Healthcare Provider: Dr. M. Jones (Endoonnologist)
Available Dates:
Available Times:
Comments
Monday, October 8, 2012
Tuesday, October 9, 2012
Wednesday, October 10, 2012
Thursday, October 11, 2012
Friday, October 12, 2012
more dates
Request Appointment
Cancel


PHR -> Mailbox -> Schedule Appointment - Mozilla Firefox
PHR » Mailbox » Appointment Scheduler
Schedule an Appointment
Physician/Healthcare Provider: Dr. M. Jones (Endoonnologist)
Available Dates: Tuesday, October 9, 2012
Available Times:
Comments
11:45 am
1:30 pm
1:45 pm
3:15 pm
4:00 pm
4:45 pm
Request Appointment
Cancel

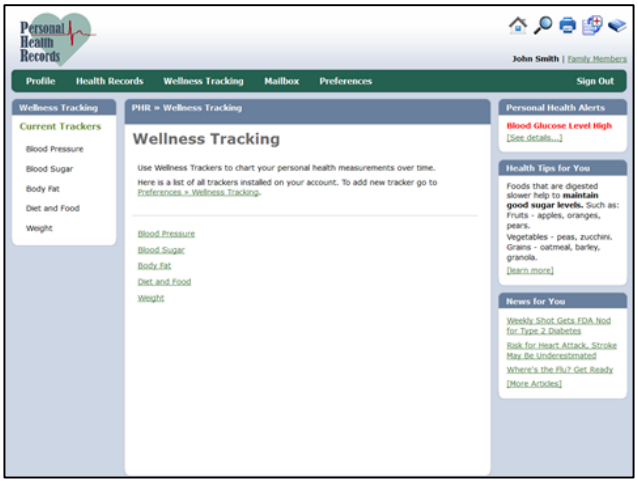

Personal Health Records
Schedule an Appointment
Physician/Healthcare Provider:
Available Dates:
Available Times:
Comments
Request Appointment
Cancel


Personal Health Records
Schedule an Appointment
Your appointment request has been sent
OK


Personal Health Records
Profile
Health Records
Wellness Tracking
Mailbox
Preferences
Sign Out
Mailbox
Select
From
Subject
Date


Blood Glucose Level Chart
High
Low
Normal Range 5-10 mmol/l
mmol/l
Share this chart with:
Send


Blood Glucose Level Chart
Your BGL chart has been sent to Dr. Jones
OK
High
Low
Normal Range 5-10 mmol/l


Personal Health Records
Profile
Health Records
Wellness Tracking
Mailbox
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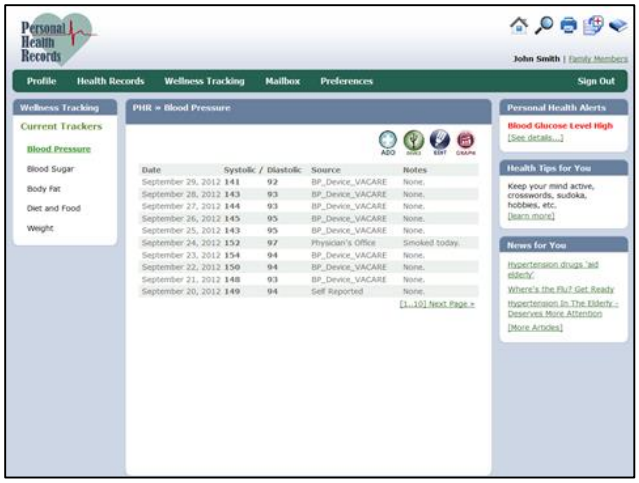
Wellness Tracking
Current Trackers
Blood Pressure
Blood Sugar
Body Fat
Diet and Food
Weight


Personal Health Records
John Smith | Family Members
Profile
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Wellness Tracking
Current Trackers
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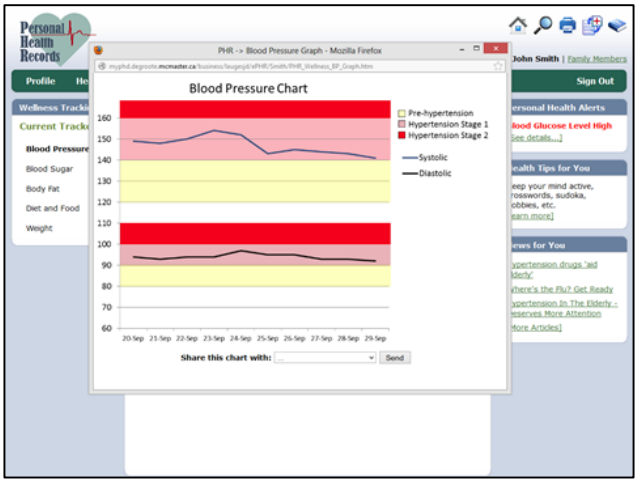
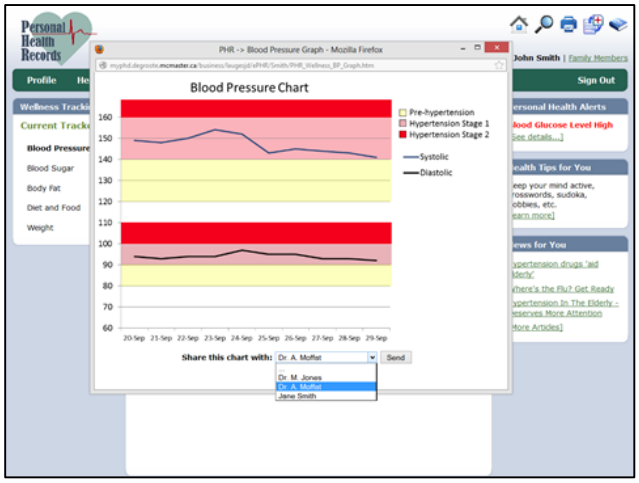
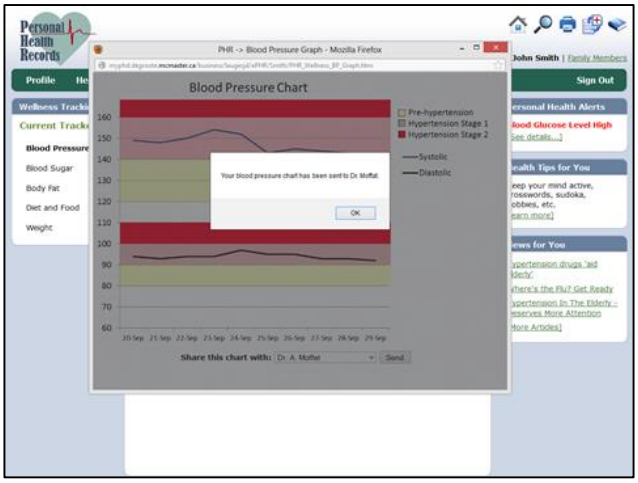
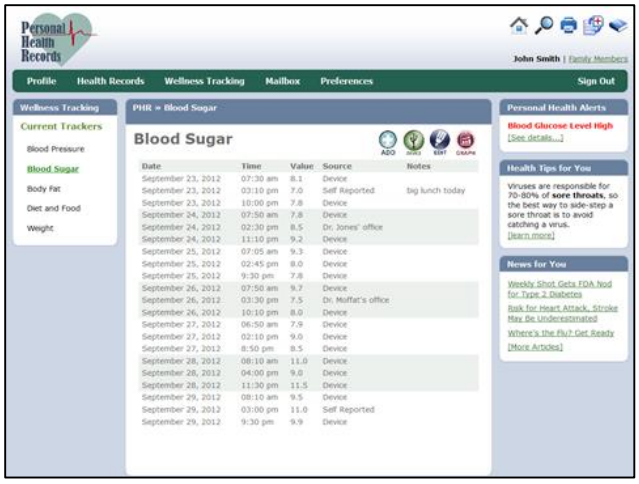
Body Fat
Diet and Food
Weight
PHR » Blood Pressure
Personal Health Alerts
Blood Glucose Level High
Health Tips for You
News for You


PHR -> Blood Pressure Graph - Mozilla Firefox
Blood Pressure Chart
Pre-hypertension
Hypertension Stage 1
Hypertension Stage 2
Systolic
Diastolic
Share this chart with:
Send


PHR -> Blood Pressure Graph - Mozilla Firefox
Blood Pressure Chart
Pre-hypertension
Hypertension Stage 1
Hypertension Stage 2
Systolic
Diastolic
Share this chart with:
Dr. A. Moffat
Send
Dr. M. Jones
Dr. A. Moffat
Jane Smith


PHR -> Blood Pressure Graph - Mozilla Firefox
Blood Pressure Chart
Your blood pressure chart has been sent to Dr. Moffat.
OK
Pre-hypertension
Hypertension Stage 1
Hypertension Stage 2
Systolic
Diastolic
Share this chart with:
Send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Diet and Food
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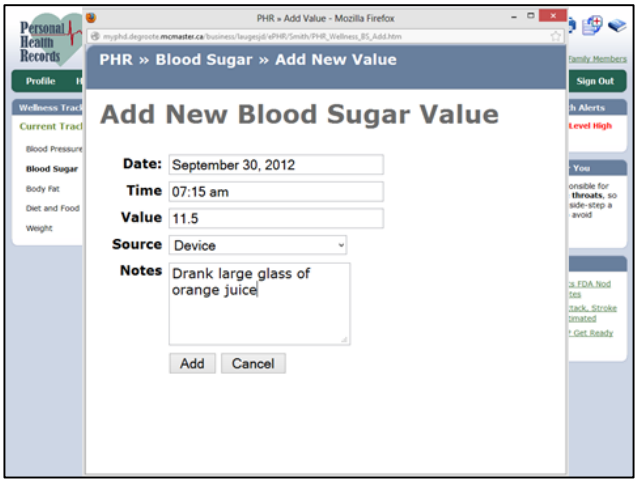
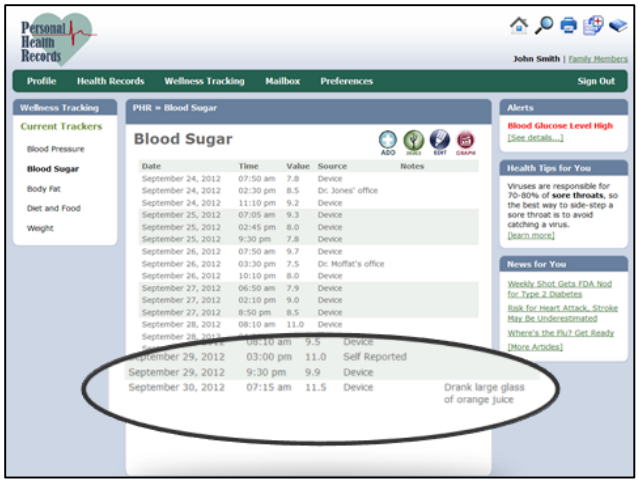
Personal Health Alerts
Blood Glucose Level High
Health Tips for You
News for You


PHR » Add Value - Mozilla Firefox
PHR » Blood Sugar » Add New Value
Add New Blood Sugar Value
Date: September 30, 2012
Time 07:15 am
Value 11.5
Source Device
Notes Drank large glass of orange juice
Add
Cancel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Blood Sugar
Date
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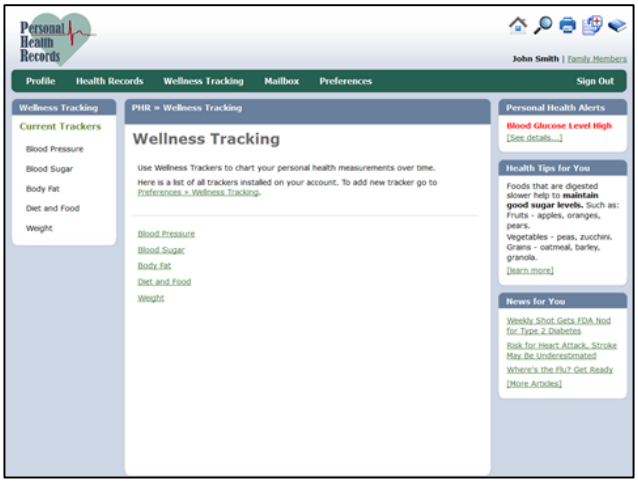
Source
Notes
September 29, 2012
03:00 pm
11.0
Self Reported
September 29, 2012
9:30 pm
9.9
Device
September 30, 2012
07:15 am
11.5
Device
Drank large glass of orange juice
Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
Viruses are responsible for 70-80% of sore throats, so the best way to side-step a sore throat is to avoid catching a virus.
[learn more]
News for You
Weekly Shot Gets FDA Nod for Type 2 Diabetes
Risk for Heart Attack, Stroke May Be Underestimated
Where's the Flu? Get Ready
[More Articles]


Personal Health Records
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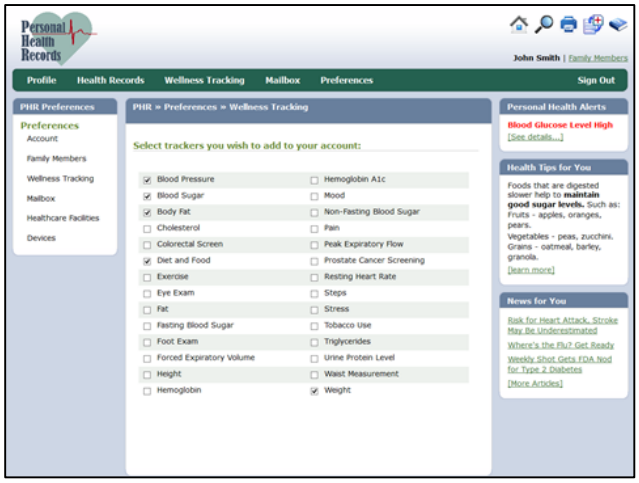
Sign Out
Wellness Tracking
Current Trackers
Blood Pressure
Blood Sugar
Body Fat
Diet and Food
Weight
PHR » Wellness Tracking
Wellness Tracking
Use Wellness Trackers to chart your personal health measurements over time.
Here is a list of all trackers installed on your account. To add new tracker go to Preferences » Wellness Tracking.
Blood Pressure
Blood Sugar
Body Fat
Diet and Food
Weight
Personal Health Alerts
Blood Glucose Level High
[See details...]
Health Tips for You
Foods that are digested slower help to maintain good sugar levels. Such as:
Fruits - apples, oranges, pears.
Vegetables - peas, zucchini.
Grains - oatmeal, barley, granola.
[learn more]
News for You
Weekly Shot Gets FDA Nod for Type 2 Diabetes
Risk for Heart Attack, Stroke May Be Underestimated
Where's the Flu? Get Ready
[More Articles]


Personal Health Records
John Smith | Family Members
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Wellness Tracking
Mailbox
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Sign Out
PHR Preferences
Preferences
Account
Family Members
Wellness Tracking
Mailbox
Healthcare Facilities
Devices
PHR » Preferences » Wellness Tracking
Select trackers you wish to add to your account:
Blood Pressure
Blood Sugar
Body Fat
Cholesterol
Colorectal Screen
Diet and Food
Exercise
Eye Exam
Fat
Fasting Blood Sugar
Foot Exam
Forced Expiratory Volume
Height
Hemoglobin
Hemoglobin A1c
Mood
Non-Fasting Blood Sugar
Pain
Peak Expiratory Flow
Prostate Cancer Screening
Resting Heart Rate
Steps
Stress
Tobacco Use
Triglycerides
Urine Protein Level
Waist Measurement
Weight
Personal Health Alerts
Blood Glucose Level High
[See details...]
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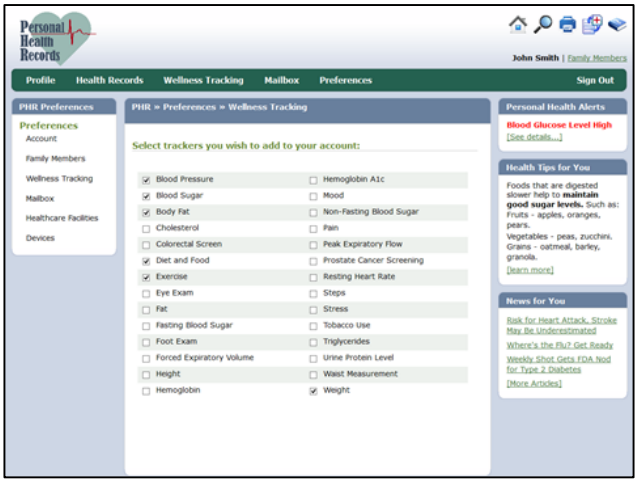
[More Articles]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Health Records
Wellness Tracking
Mailbox
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Sign Out
PHR Preferences
Preferences
Account
Family Members
Wellness Tracking
Mailbox
Healthcare Facilities
Devices
PHR » Preferences » Wellness Tracking
Select trackers you wish to add to your account:
Blood Pressure
Blood Sugar
Body Fat
Cholesterol
Colorectal Screen
Diet and Food
Exercise
Eye Exam
Fat
Fasting Blood Sugar
Foot Exam
Forced Expiratory Volume
Height
Hemoglobin
Hemoglobin A1c
Mood
Non-Fasting Blood Sugar
Pain
Peak Expiratory Flow
Prostate Cancer Screening
Resting Heart Rate
Steps
Stress
Tobacco Use
Triglycerides
Urine Protein Level
Waist Measurement
Weight
Personal Health Alerts
Blood Glucose Level High
[See details...]
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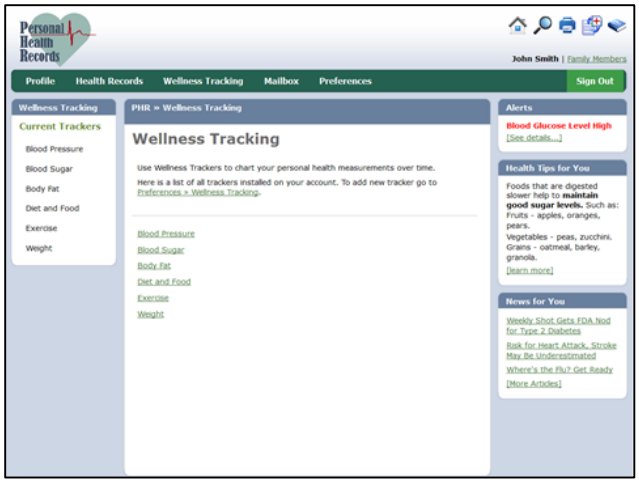
[More Articles]


Personal Health Records
John Smith | Family Members
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Health Records
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Wellness Tracking
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Body Fat
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Wellness Tracking
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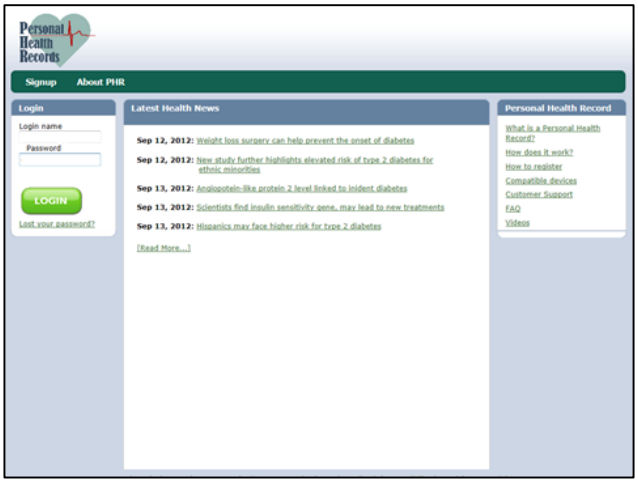
Where's the Flu? Get Ready
[More Articles]


Personal Health Records
Signup
About PHR
Login
Login name
Password
LOGIN
Lost your password?
Latest Health News
Sep 12, 2012: Weight loss surgery can help prevent the onset of diabetes
Sep 12, 2012: New study further highlights elevated risk of type 2 diabetes for ethnic minorities
Sep 13, 2012: Angiopoietin-like protein 2 level linked to incident diabetes
Sep 13, 2012: Scientists find insulin sensitivity gene, may lead to new treatments
Sep 13, 2012: Hispanics may face higher risk for type 2 diabetes
[Read More...]
Personal Health Record
What is a Personal Health Record?
How does it work?
How to register
Compatible devices
Customer Support
FAQ
Videos

Studies show that people with Type 2 Diabetes who used an **ePHR** for the self-management of their chronic disease:

- *Were more prepared for and experienced improved visits with their physicians*
- *Achieved a significant reduction (averaging 0.7) in their HbA1c levels. For people with Type 2 Diabetes, this reflects a 5 –10% drop in their HbA1c level.*

Thank you for watching this video

Please click the 'Next' button to continue the survey.

Appendix B – Measurement Instruments

Construct and Scale	Source	Specific Items
Severity 7-point Likert (Strongly Disagree to Strongly Agree)	(Norman, et al., 2003)	SEV1 I am concerned about my Type 2 Diabetes. SEV2 I experience anxiety as a result of my Type 2 Diabetes. SEV3 My Type 2 Diabetes is a source of stress for me. SEV4 I am worried about my Type 2 Diabetes. SEV5 I believe that my Type 2 Diabetes is a serious medical condition. SEV6 My health is at risk due to my Type 2 Diabetes.
Vulnerability 7-point Likert (Strongly Disagree to Strongly Agree)	(Norman, et al., 2003)	VUL1 I worry about Type 2 Diabetes related complications that I might develop in the future. VUL2 I am concerned about developing further complications from my Type 2 Diabetes. VUL3 I worry about Type 2 Diabetes related complications that I might presently have, but have not yet been diagnosed with. VUL4 I am concerned about my vulnerability to further Type 2 Diabetes complications.
PHR Adoption Intention 7-point Likert (Strongly Disagree to Strongly Agree)	(Venkatesh, et al., 2003)	ADOPT1 If an ePHR was available to me, I predict I would use it to help self-manage my Type 2 Diabetes. ADOPT2 If an ePHR was available to me, I intend to use it to help self-manage my Type 2 Diabetes. ADOPT3 If an ePHR was available to me, I plan to use it to help self-manage my Type 2 Diabetes.
Perceived Task Technology Fit 7-point Likert (Strongly Disagree to Strongly Agree)	(Lin & Huang, 2008)	PTTF1 I believe the functionalities of an ePHR would be adequate in assisting me to perform Type 2 Diabetes self-management tasks. PTTF2 I believe the functionalities of an ePHR would be appropriate in assisting me to perform Type 2 Diabetes self-management tasks. PTTF3 I believe the functionalities of an ePHR would be useful in assisting me to perform Type 2 Diabetes self-management tasks. PTTF4 I believe the functionalities of an ePHR would be compatible with Type 2 Diabetes self-management tasks. PTTF5 I believe the functionalities of an ePHR would be helpful in assisting me to perform Type 2 Diabetes self-management tasks. PTTF6 I believe the functionalities of an ePHR would be sufficient in assisting me to perform Type 2 Diabetes self-management tasks. PTTF7 I believe the functionalities of an ePHR would make Type 2 Diabetes self-management tasks easier. PTTF8 I believe the functionalities of an ePHR would be a good fit for Type 2 Diabetes self-management tasks. * Grayed items indicate those removed due to high cross-loadings.

Self-Efficacy 7-point Likert (Strongly Disagree to Strongly Agree)	(Venkatesh, et al., 2003)	SE1 I believe I could use an ePHR if there was no one around to tell me what to do as I go. SE2 I believe I could use an ePHR if I could call someone for help if I got stuck. SE3 I believe I could use an ePHR if I had a lot of time to learn the ePHR system. SE4 I believe I could use an ePHR if I only had the built-in help facility for assistance.
Response Efficacy 7-point Likert (Strongly Disagree to Strongly Agree)	(Norman, et al., 2003)	RE1 Using an ePHR for Type 2 Diabetes self-management could reduce my chances of having health problems. RE2 My Type 2 Diabetes condition could be maintained or improved if self-managed using an ePHR. RE3 Using an ePHR for Type 2 Diabetes self-management could provide me with greater control of my blood glucose levels and my Type 2 Diabetes. RE4 Overall, I feel that self-management of my Type 2 Diabetes using an ePHR could have a positive impact on my health.
Response Costs 7-point Likert (Strongly Disagree to Strongly Agree)	(Milne, et al., 2002)	RC1 I would be discouraged from using an ePHR because it would take too much time. RC2 I am concerned about the privacy and security of my health information if I use an ePHR. RC3 I am concerned that it would be expensive to use an ePHR. RC4 I feel the potential costs of using an ePHR would outweigh the benefits.
Patient Activation Measure 4-Point Likert (Disagree Strongly to Agree Strongly, Not Applicable included as an option)	(Hibbard, et al., 2005)	PAM1 When all is said and done, I am the person who is responsible for managing my health condition. PAM2 Taking an active role in my own health care is the most important factor in determining my health and ability to function. PAM3 I am confident that I can take actions that will help prevent or minimize some symptoms or problems associated with my health condition. PAM4 I know what each of my prescribed medications do. PAM5 I am confident that I can tell when I need to go get medical care and when I can handle a health problem myself. PAM6 I am confident that I can tell my health care provider concerns I have even when he or she does not ask. PAM7 I am confident that I can follow through on medical treatments I need to do at home. PAM8 I understand the nature and causes of my health condition(s) PAM9 I know the different medical treatment options available for my health condition. PAM10 I have been able to maintain the lifestyle changes for my health that I have made. PAM11 I know how to prevent further problems with my health condition. PAM12 I am confident that I can figure out solutions when new situations or problems arise with my health condition. PAM13 I am confident that I can maintain lifestyle changes like diet and exercise even during times of stress.

Appendix C – Letter of Consent

LETTER OF INFORMATION / CONSENT

Adoption of Electronic Personal Health Records by Persons with Type 2 Diabetes

Principal Investigator:
Dr. Khaled Hassanein
DeGroote School of Business
McMaster University
Hamilton, Ontario, Canada
(905) 525-9140 ext. 23956
E-mail: hassank@mcmaster.ca

Student Investigator:
John Laugesen
DeGroote School of Business
McMaster University
Hamilton, Ontario, Canada
(905) 525-9140 ext. 26216
E-mail: laugesjd@mcmaster.ca

Purpose of the Study
You are asked to participate in a research study conducted by Dr. Khaled Hassanein and John Laugesen (PhD Candidate) at McMaster University, Hamilton. If you have any questions or concerns about the research, please feel free to contact John Laugesen at 905-525-9140 ext. 26216 or laugesjd@mcmaster.ca

What will happen during the study?
This survey will last approximately 30 minutes. If you volunteer to participate in this study, you will be asked to:

- Give your consent at the bottom of this page.
- View short video clips outlining Type 2 Diabetes complications and some aspects of using electronic Personal Health Records (ePHRs).
- Answer questions about your impressions regarding Type 2 diabetes, self-management and electronic Personal Health Records (ePHRs).
- Provide basic demographic information including age, gender, etc

You are welcome to ask for a written report on the results of this study at the end of the project (which may take several months to complete) from John Laugesen (laugesjd@mcmaster.ca)

Are there any risks to doing this study?
As a participant in this study, you may be exposed to potentially unsettling information regarding possible complications of Type 2 diabetes which may worry or upset you. If you feel this type of

information will upset you, it is advised that you do not participate in this study. If you choose to participate, you do not need to answer questions that you do not want to answer or that make you feel uncomfortable by withdrawing (stop taking part) at any time.

Are there any benefits to doing this study?

This study may contribute to physicians, persons with Type 2 diabetes, other persons with chronic diseases and society in general. The results of this study may be useful to physicians via improvements to the health of their patients, more effective patient-physician appointments and a reduction in the time requirements that chronic patients place on physicians. From a patient standpoint, results from this study can potentially assist chronic disease sufferers via improving their health condition, quality of life, etc. From a societal standpoint, results from this study could potentially reduce some of the economic costs associated with chronic disease health care.

Payment or Reimbursement

Upon completion of this survey you will be compensated as per your email from Research Now AIR MILES Opinions.

Who will know what I said or did in the study?

Any information that is obtained in connection with this study will remain confidential. Although the data collected from each participant's responses will be directly used in data analysis, reporting of findings will not identify specific individuals. Findings may be categorized according to subject groups but no data pertaining to individual responses will be released in such a way that participants can be identified. The information/data you provide will be kept on a password protected computer located in a locked room. Participant identity information (i.e., email address for compensation purposes) will be kept in a separate file than participant survey question responses, and therefore there will be no way for anyone, including the researcher to associate specific responses with an individual participant. Once the study has been completed, the data will be destroyed.

What if I change my mind about being in the study?

You may withdraw your consent at any time and discontinue participation without penalty. At the bottom of each question page, you have the option to 'Exit and clear' the survey. You are not waiving any legal claims, rights or remedies because of your participation in this research study. This study has been reviewed by the McMaster University Research Ethics Board and received ethics clearance. If you have concerns or questions about your rights as a participant or about the way the study is conducted, please contact:

McMaster Research Ethics Secretariat
Telephone: (905) 525-9140 ext. 23142
c/o Research Office for Administrative Development and Support
E-mail: ethicsoffice@mcmaster.ca

By clicking on the "Next" button below, you agree to participate in this study, and that: "I understand the information provided for the study, McMaster Electronic Personal Health Record Study, as described herein. My questions have been answered to my satisfaction."

If you do not agree to participate in the study, either close your browser window or navigate away from this page.

Appendix D – Online Survey Questions

1. Do you currently have Type 2 Diabetes?

Please choose **only one** of the following:

- ○ Yes
- ○ No

* if 'No', respondent did not proceed with remainder of the survey

2. Prior to your participation in this research study, we need to understand your level of knowledge regarding electronic Personal Health Records (ePHRs). How would you rate your level of knowledge about electronic Personal Health Records (ePHRs)?

Please choose **only one** of the following:

- ○ No Knowledge (I have never heard of ePHRs before.)
- ○ Limited Knowledge (I have heard of ePHRs but don't fully understand what they do.)
- ○ Good Knowledge (I know what ePHRs are and have a good understanding of what they do.)
- ○ Advanced Knowledge (I know a lot about ePHRs and/or have used an ePHR before.)

* if 'Good Knowledge' or 'Advanced Knowledge', respondent did not proceed with remainder of the survey

Demographic Quota Questions

3. What is your current age?

Please choose **only one** of the following:

- ○ 18-29
- ○ 30-39
- ○ 40-49
- ○ 50-59
- ○ 60-69
- ○ 70+

4. What is your gender?

Please choose **only one** of the following:

- ○ Female
- ○ Male

* Questions 3 and 4 used to ensure demographics of sample closely matched demographics of the population with Type 2 Diabetes.

Diabetes Knowledge Questions

5. How would you rate the severity of your Type 2 Diabetes?

Please choose **only one** of the following:

- ○ Mild
- ○ Mild to Moderate
- ○ Moderate
- ○ Moderate to Severe
- ○ Severe

6. How would you rate your knowledge about Type 2 Diabetes?

Please choose **only one** of the following:

- ○ Poor
- ○ Fair
- ○ Good
- ○ Very Good
- ○ Excellent

7. How would you rate the level of control you have over your Type 2 Diabetes?

Please choose **only one** of the following:

- ○ Very Poorly Controlled
- ○ Poorly Controlled
- ○ Moderately Controlled
- ○ Well Controlled
- ○ Very Well Controlled

8. How long has it been since you were diagnosed with Type 2 Diabetes?

Please choose **only one** of the following:

- ○ <1 Year
- ○ 1-4 Years
- ○ 5-9 Years
- ○ 10-19 Years
- ○ 20-29 Years
- ○ 30+ Years

* Diabetes Complications Video is shown at this point.

Severity (SEV)

9. Please think about how you personally feel with regards to your Type 2 Diabetes as you answer the following questions.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
I am concerned about my Type 2 Diabetes.	○	○	○	○	○	○	○
I experience anxiety as a result of my Type 2 Diabetes.	○	○	○	○	○	○	○
My Type 2 Diabetes is a source of stress for me.	○	○	○	○	○	○	○
I am worried about my Type 2 Diabetes.	○	○	○	○	○	○	○
I believe that my Type 2 Diabetes is a serious medical condition.	○	○	○	○	○	○	○
My health is at risk due to my Type 2 Diabetes.	○	○	○	○	○	○	○

Vulnerability (VUL)

10. Please think about how you personally feel with regards to your Type 2 Diabetes condition in the future as you answer the following questions.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
I worry about Type 2 Diabetes related complications that I might develop in the future.	○	○	○	○	○	○	○
I am concerned about developing further complications from my Type 2 Diabetes.	○	○	○	○	○	○	○
I worry about Type 2 Diabetes related complications that I might presently have, but have not yet been diagnosed with.	○	○	○	○	○	○	○
I am concerned about my vulnerability to further Type 2 Diabetes complications.	○	○	○	○	○	○	○

Manipulation Check – Diabetes Complications

11. The following questions are based on the video clip you watched a few moments ago.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
The video clip increased my level of concern about the severity of my Type 2 Diabetes.	○	○	○	○	○	○	○
The video clip increased my level of concern about my vulnerability to complications that may arise from my Type 2 Diabetes.	○	○	○	○	○	○	○
The video clip increased my level of concern about current and future health threats posed by my Type 2 Diabetes condition and the associated complications.	○	○	○	○	○	○	○

* ePHR Education Video is shown at this point.

Adoption Intention (ADOPT)

12. The following questions are concerned with your thoughts about the potential of using an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
If an ePHR was available to me, I predict I would use it to help self-manage my Type 2 Diabetes.	○	○	○	○	○	○	○
If an ePHR was available to me, I intend to use it to help self-manage my Type 2 Diabetes.	○	○	○	○	○	○	○
If an ePHR was available to me, I plan to use it to help self-manage my Type 2 Diabetes.	○	○	○	○	○	○	○

Response Efficacy (RE)

13. The following questions are concerned with the use of an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
Using an ePHR for Type 2 Diabetes self-management could reduce my chances of having health problems.	○	○	○	○	○	○	○
My Type 2 Diabetes condition could be maintained or improved if self-managed using an ePHR.	○	○	○	○	○	○	○
Using an ePHR for Type 2 Diabetes self-management could provide me with greater control of my blood glucose levels and my Type 2 Diabetes.	○	○	○	○	○	○	○
Overall, I feel that self-management of my Type 2 Diabetes using an ePHR could have a positive impact on my health.	○	○	○	○	○	○	○

Perceived Task Technology Fit (PTTF)

14. The following questions are concerned with the use of an electronic Personal Health Record (ePHR) in assisting you to perform Type 2 Diabetes self-management task(s).

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
I believe the functionalities of an ePHR would be adequate in assisting me to perform Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would be appropriate in assisting me to perform Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○

I believe the functionalities of an ePHR would be useful in assisting me to perform Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would be compatible with Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would be helpful in assisting me to perform Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would be sufficient in assisting me to perform Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would make Type 2 Diabetes self-management tasks easier.	○	○	○	○	○	○	○
I believe the functionalities of an ePHR would be a good fit for Type 2 Diabetes self-management tasks.	○	○	○	○	○	○	○

Self-Efficacy (SE)

15. The following questions are concerned with your ability to use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
I believe I could use an ePHR if there was no one around to tell me what to do as I go.	○	○	○	○	○	○	○
I believe I could use an ePHR if I could call someone for help if I got stuck.	○	○	○	○	○	○	○
I believe I could use an ePHR if I had a lot of time to learn the ePHR system.	○	○	○	○	○	○	○
I believe I could use an ePHR if I only had the built-in help facility for assistance.	○	○	○	○	○	○	○

Patient Activation Measure (PAM)

16. Below are some statements that people sometimes make when they talk about their health. Please indicate how much you agree or disagree with each statement as it applies to you personally by selecting your answer. Your answers should be what is true for you and not what you think others want you to say.
If the statement does not apply to you, select Not Applicable (N/A).

Please choose the appropriate response for each item:

	Disagree Strongly	Disagree	Agree	Agree Strongly	Not Applicable (N/A)
When all is said and done, I am the person who is responsible for managing my health condition.	○	○	○	○	○
Taking an active role in my own health care is the most important factor in determining my health and ability to function.	○	○	○	○	○
I am confident that I can take actions that will help prevent or minimize some symptoms or problems associated with my health condition.	○	○	○	○	○
I know what each of my prescribed medications do.	○	○	○	○	○
I am confident that I can tell when I need to go get medical care and when I can handle a health problem myself.	○	○	○	○	○
I am confident that I can tell my health care provider concerns I have even when he or she does not ask.	○	○	○	○	○
I am confident that I can follow through on medical treatments I need to do at home.	○	○	○	○	○
I understand the nature and causes of my health condition(s).	○	○	○	○	○

I know the different medical treatment options available for my health condition.	○	○	○	○	○
I have been able to maintain the lifestyle changes for my health that I have made.	○	○	○	○	○
I know how to prevent further problems with my health condition.	○	○	○	○	○
I am confident that I can figure out solutions when new situations or problems arise with my health condition.	○	○	○	○	○
I am confident that I can maintain lifestyle changes like diet and exercise even during times of stress.	○	○	○	○	○

Response Costs (RC)

17. The following questions are concerned with the potential costs associated with using an electronic Personal Health Record (ePHR).

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
I would be discouraged from using an ePHR because it would take too much time.	○	○	○	○	○	○	○
I am concerned about the privacy and security of my health information if I use an ePHR.	○	○	○	○	○	○	○
I am concerned that it would be expensive to use an ePHR.	○	○	○	○	○	○	○
I feel the potential costs of using an ePHR would outweigh the benefits.	○	○	○	○	○	○	○

Manipulation Check - ePHR

18. The following questions are based on the video clip you watched earlier about electronic Personal Health Records (ePHRs).

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Somewhat Disagree	Neutral (Neither Agree Nor Disagree)	Somewhat Agree	Agree	Strongly Agree
After watching the video clip about ePHRs, I feel I have a better understanding of how to use an ePHR to assist in the self-management of my Type 2 Diabetes.	○	○	○	○	○	○	○
After watching the video clip about ePHRs, I feel I have a better understanding about the benefits of using an ePHR to assist in the self-management of my Type 2 Diabetes.	○	○	○	○	○	○	○
After watching the video clip about ePHRs, I feel more confident that I would be able to use an ePHR to assist in the self-management of my Type 2 Diabetes.	○	○	○	○	○	○	○

Demographic Questions

19. What is your marital status?

Please choose **only one** of the following:

○ Single, never legally married
○ Legally married (and not separated)
○ Separated, but still legally married
○ Living with a partner
○ Divorced
○ Widowed

20. What is the highest level of education you have completed?

Please choose **only one** of the following:

- ○ Did not complete high school
- ○ High School
- ○ Some College or University
- ○ College or University Degree/Diploma
- ○ Graduate Degree (Masters or PhD)

21. What is your annual income?

Please choose **only one** of the following:

- ○ < $10,000
- ○ $10,000 - $24,999
- ○ $25,000 - $49,999
- ○ $50,000 - $74,999
- ○ $75,000 - $99,999
- ○ > $100,000

22. Which best describes your current employment situation?

Please choose **only one** of the following:

- ○ Employed full-time (35+ hours/week)
- ○ Employed part-time/casual (less than 35 hours/week)
- ○ Self-employed
- ○ Home maker
- ○ Student (full-time or part-time)
- ○ Retired
- ○ Not currently employed

Health Related Questions

23. How would you rate your current health in general?

Please choose **only one** of the following:

- ○ Poor
- ○ Fair
- ○ Good
- ○ Very Good
- ○ Excellent

24. How would you rate your knowledge about your health in general?

Please choose **only one** of the following:

- ○ Poor
- ○ Fair
- ○ Good
- ○ Very Good
- ○ Excellent

Open-Ended Questions

25. What are the top three reasons why you would adopt and use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes?

26. What are the top three reasons why you would not adopt and use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes?

27. What effects did the Diabetes information that was presented to you in the first video clip have on your decision regarding whether or not you would adopt and use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes?

28. What effects did the electronic Personal Health Record (ePHR) information that was presented to you in the second video clip have on your decision regarding whether or not you would adopt and use an electronic Personal Health Record (ePHR) to assist you in the self-management of your Type 2 Diabetes?

29. What other thoughts, if any, do you have with respect to self-managing your Type 2 Diabetes through the use of an electronic Personal Health Record (ePHR)?

30. How much would you be willing to pay per month for use of an electronic Personal Health Record (ePHR)?

Appendix E – Pilot and Main Study Flyer

McMaster University

DeGroote SCHOOL OF BUSINESS

PARTICIPANTS NEEDED FOR RESEARCH ON *'ELECTRONIC PERSONAL HEALTH RECORD ADOPTION AMONG PERSONS WITH TYPE 2 DIABETES'*

We are seeking volunteers 18 years and older with Type 2 diabetes to participate in a study on factors associated with the adoption of electronic Personal Health Records (ePHRs). Participants in this study must not have previously used an ePHR and should have limited to no knowledge about ePHRs.

The questionnaire for this study is available for completion on the Internet. Please note that participation in this study is completely voluntary and confidential. Total time to complete this study is approximately 30 minutes. As a thank you for your participation, you will receive a $10 gift card to Tim Hortons. To volunteer for this study, please go to:

http://phd.degroote.mcmaster.ca/laugesjd/ePHR/

OR

Email: John Laugesen at laugesjd@mcmaster.ca

For more information about this study, please contact:
John Laugesen, McMaster University
905-525-9140 Ext. 26216 or
Email: *laugesjd@mcmaster.ca*

This study has been reviewed by, and received ethics clearance by the McMaster Research Ethics Board.

Appendix F – Pilot and Main Study Poster

McMaster University

DeGroote SCHOOL OF BUSINESS

PARTICIPANTS NEEDED FOR RESEARCH ON '*ELECTRONIC PERSONAL HEALTH RECORD ADOPTION AMONG PERSONS WITH TYPE 2 DIABETES*'

We are seeking volunteers 18 years and older with Type 2 diabetes to participate in a study on factors associated with the adoption of electronic Personal Health Records (ePHRs). Participants in this study must not have previously used an ePHR and should have limited to no knowledge about ePHRs.

The questionnaire for this study is available for completion on the Internet. Please note that participation in this study is completely voluntary and confidential. Total time to complete this study is approximately 30 minutes. As a thank you for your participation, you will receive a $10 gift card to Tim Hortons. To volunteer for this study, please go to http://phd.degroote.mcmaster.ca/laugesjd/ePHR/ or email John Laugesen at laugesjd@mcmaster.ca

For more information about this study, please contact:
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905-525-9140 Ext. 26216 or
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Appendix G – Pilot Study Posting on www.tudiabetes.org

Earn a $10 Gift Card for Participating in a Survey!

Posted by laugesen on July 24, 2012 at 9:05pm in Diabetes trials, studies and surveys View Discussions

Hi, my name is John Laugesen, and I am a PhD Student at McMaster University in Hamilton, Canada. I have been a member of TuDiabetes.org since April of this year, when I was diagnosed as pre-diabetic (HbA1c of 6.1)

I am currently completing my PhD thesis work, which examines the factors involved in the adoption of Electronic Personal Health Records (ePHRs) by persons with Type 2 Diabetes. Don't worry if you don't know what ePHRs are, as the study will explain that!

The study involves participants watching a short video, and then filling out a survey. The entire process can be conducted online. The study has been approved by the McMaster Research Ethics Board, and has also been approved by TuDiabetes Administration for posting on this site.

Participants in the survey will receive a $10 Gift Card (from Amazon.com for US and International residents, and from Tim Hortons for Canadian residents). The entire process takes approximately 30 minutes.

If you (or someone you know) have Type 2 Diabetes, are18 years or older, and are interested in completing this survey, this can be done at:

http://phd.degroote.mcmaster.ca/laugesjd/ePHR/

or contact me (laugesjd@mcmaster.ca)

Appendix H – Main Study Postings on www.tudiabetes.org

Interested in a Chance to Earn a $100 Amazon Gift Card?

Posted by laugesen on November 14, 2012 at 7:55am in Diabetes trials, studies and surveys

View Discussions

Hi, my name is John Laugesen, and I am a PhD Student at McMaster University in Hamilton, Canada. I have been a member of TuDiabetes.org since April of this year, when I was diagnosed as pre-diabetic (HbA1c of 6.1)

I am currently completing my PhD thesis work, which examines the factors involved in the adoption of Electronic Personal Health Records (ePHRs) by persons with **Type 2 Diabetes**. Don't worry if you don't know what ePHRs are, as the study will explain that!

The study involves participants watching a two video clips, and answering a set of survey questions. The entire process can be conducted online. The study has been approved by the McMaster Research Ethics Board, and has also been approved by TuDiabetes Administration for posting on this site.

Participants in the survey will be entered into a draw for 1 of 6 prizes (2 - $100 Amazon gift cards and 4 - $50 Amazon gift cards are available). The entire process takes approximately 25-30 minutes.

If you have already completed my earlier pilot survey in July of this year, or if you have already received an email invite to participate in this current survey, please do not click the link below, as you can only complete the survey process once.

If you (or someone you know) have **Type 2 Diabetes**, are 18 years or older, have not previously participated in this study, and are interested in completing this survey, please click the following link:

http://myphd.degroote.mcmaster.ca/business/laugesjd/

or contact me (laugesjd@mcmaster.ca)

Earn a $10 Gift Card for Participating in a Survey!

Posted by laugesen on November 20, 2012 at 2:18pm in Diabetes trials, studies and surveys

View Discussions

We have changed the compensation for the Electronic Personal Health Records (ePHR) Adoption Study, and rather than holding a draw for prizes, all participants completing the survey will now receive a $10 Gift Card from Amazon.

Appendix I – Variable/Construct Summary (i.e., Names and Descriptions)

Model Constructs

SEV – The respondent's perceptions of how severe the risks posed by their Type 2 Diabetes are to their health.

VUL – The respondent's perceptions of how susceptible they feel to the threats posed by their Type 2 Diabetes.

ADOPT – The respondent's perceptions about their potential intentions of adopting an ePHR to assist them in the self-management of their Type 2 Diabetes.

PTTF – The respondent's perceptions of how well the functionalities and capabilities of an ePHR match the requirements of the task of Type 2 Diabetes self-management.

SE – The respondent's beliefs in their ability to use an ePHR for Type 2 Diabetes self-management.

RE – The respondent's beliefs that the use of an ePHR will lead to better disease self-management and improved health outcomes.

RC – The respondent's perceptions of the potential costs, both monetary and other (e.g., time, privacy, etc.) incurred in performing Type 2 Diabetes self-management using an ePHR.

PAM – The respondent's assessment of their knowledge, skill, and confidence for self-management of their health or chronic condition.

Demographics:

AGE – Self-reported age, with 6 ordinal responses (18-29, 30-39, 40-49, 50-59, 60-69, 70+); Mandatory question.

GENDER – Self-reported gender (either Male or Female); Mandatory question.

INCOME – Self-reported annual income with 6 ordinal responses (< $10,000, $10,000 - $24,999, $25,000 - $49,999, $50,000 - $74,999, $75,000 - $99,999, > $100,000); Optional Question.

EDUCATION – Self-reported highest level of education completed, with 5 ordinal responses (Did not complete high school, High School, Some College or University, College or University Degree/Diploma, Graduate Degree (Masters or PhD)); Optional question.

EMPLOYMENT – Self-reported current employment situation, with 7 categorical responses (Employed full-time (35+ hours/week), Employed part-time/casual (less than 35 hours/week), Self-employed, Home maker, Student (full-time or part-time), Retired, Not currently employed); Optional question.

MARITAL – Self-reported marital status, with 6 categorical responses (Single, never legally married, Legally married (and not separated), Separated, but still legally married, Living with a partner, Divorced, Widowed); Optional question.

Type 2 Diabetes Specific:

T2KNOWLEDGE – Self-reported knowledge respondent has about Type 2 Diabetes, with 5 ordinal responses (Poor, Fair, Good, Very Good, Excellent); Optional question.

T2CONTROL – Self-reported level of control the respondent has over their Type 2 Diabetes, with 5 ordinal responses (Very Poorly Controlled, Poorly Controlled, Moderately Controlled, Well Controlled, Very Well Controlled); Optional question.

T2DURATION – Self-reported length of time the since the respondent was diagnosed with their Type 2 Diabetes, with 6 ordinal responses (<1 Year, 1-4 Years, 5-9 Years, 10-19 Years, 20-29 Years, 30+ Years); Optional question.

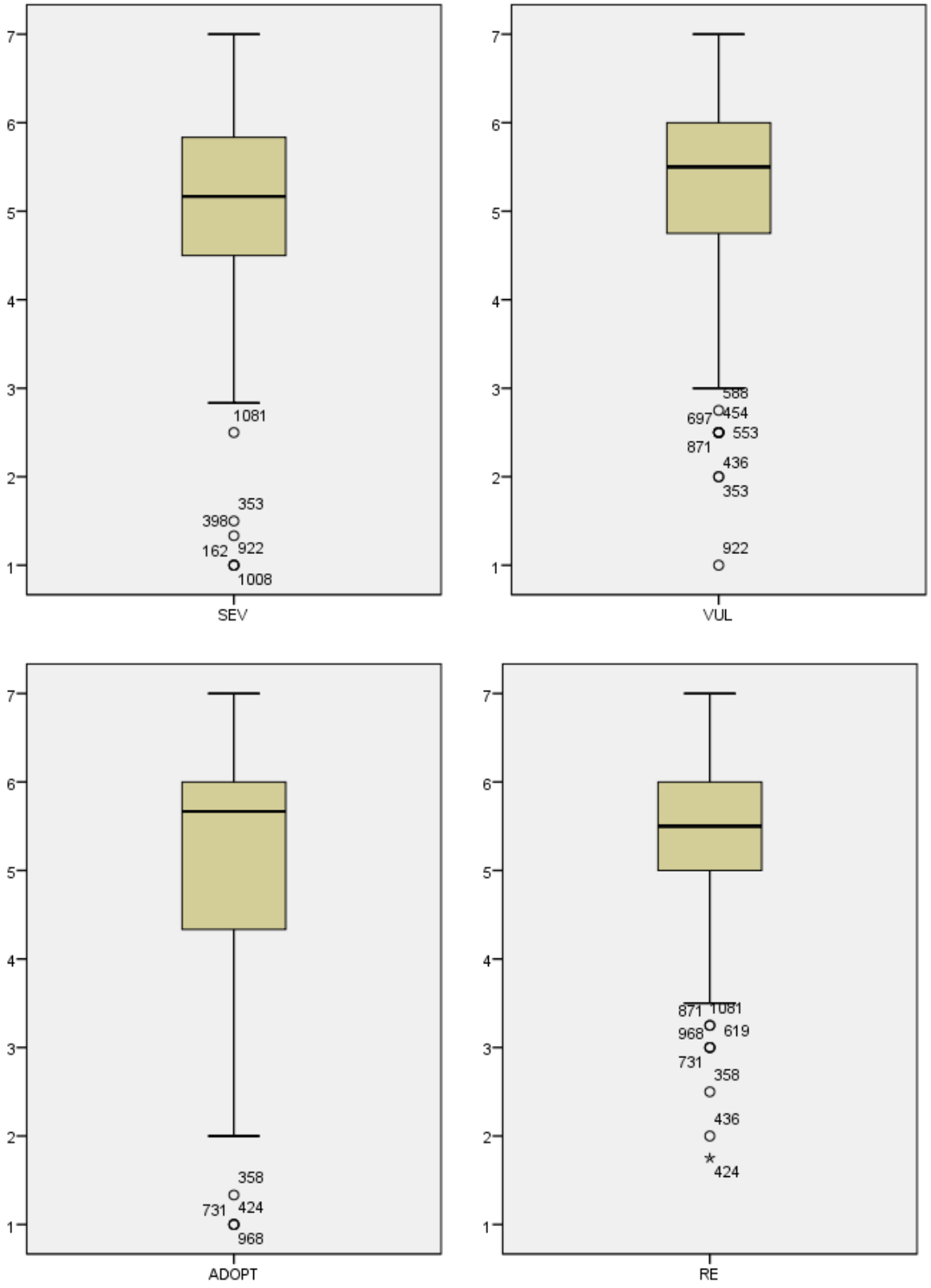
T2SEVERITY – Self-reported assessment regarding the severity of the respondent's Type 2 Diabetes, with 5 ordinal responses (Mild, Mild to Moderate, Moderate, Moderate to Severe, Severe); Optional question.

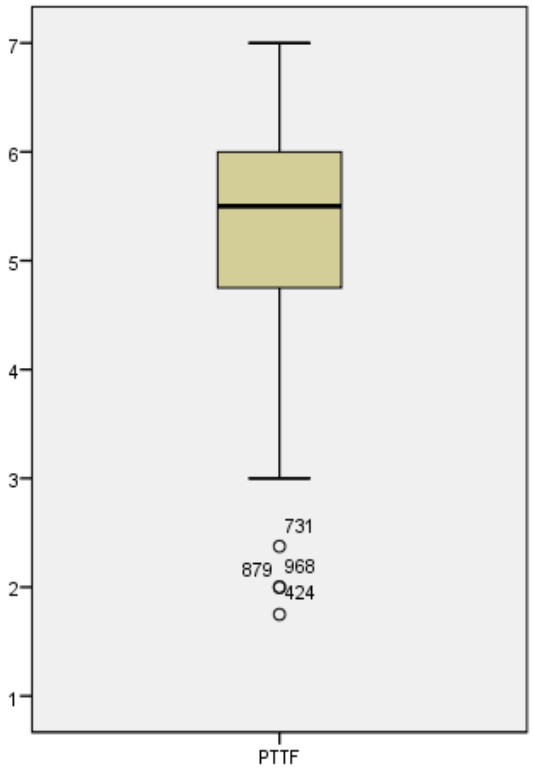
General Health Related:

GENERALHEALTH – Self-reported assessment of the respondent's general health condition, with 5 ordinal responses (Poor, Fair, Good, Very Good, Excellent); Optional question.

HEALTHKNOWLEDGE – Self-reported assessment of the level of knowledge the respondent has regarding their health in general, with 5 ordinal responses (Poor, Fair, Good, Very Good, Excellent); Optional question.

Appendix J – Composite/Indicator Boxplots

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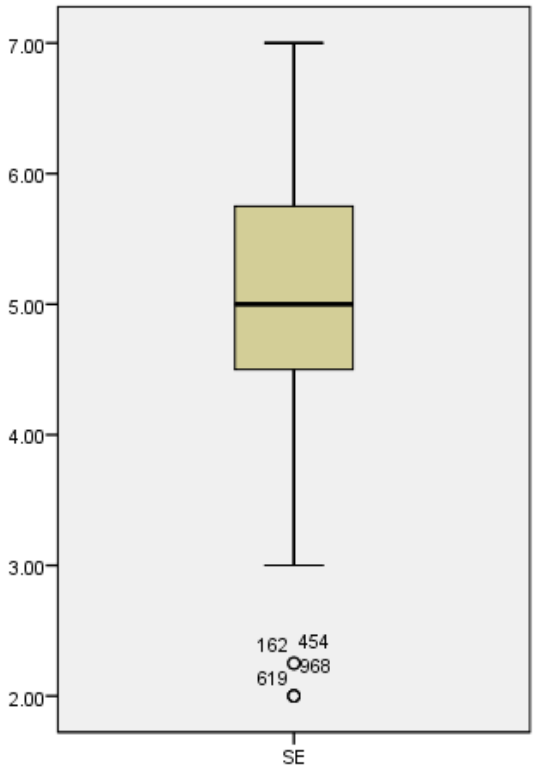
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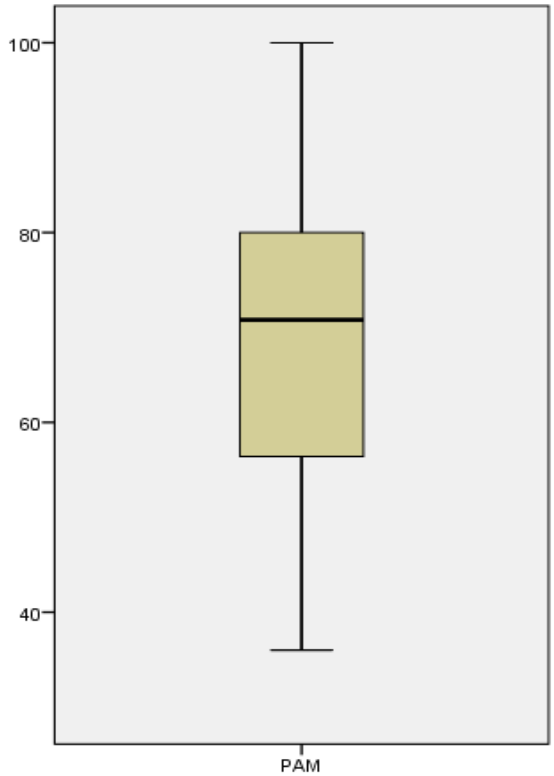
SE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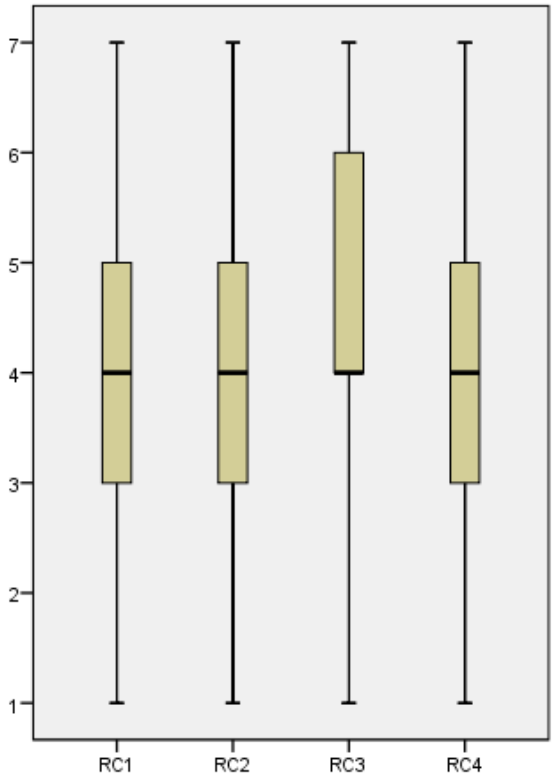
PAM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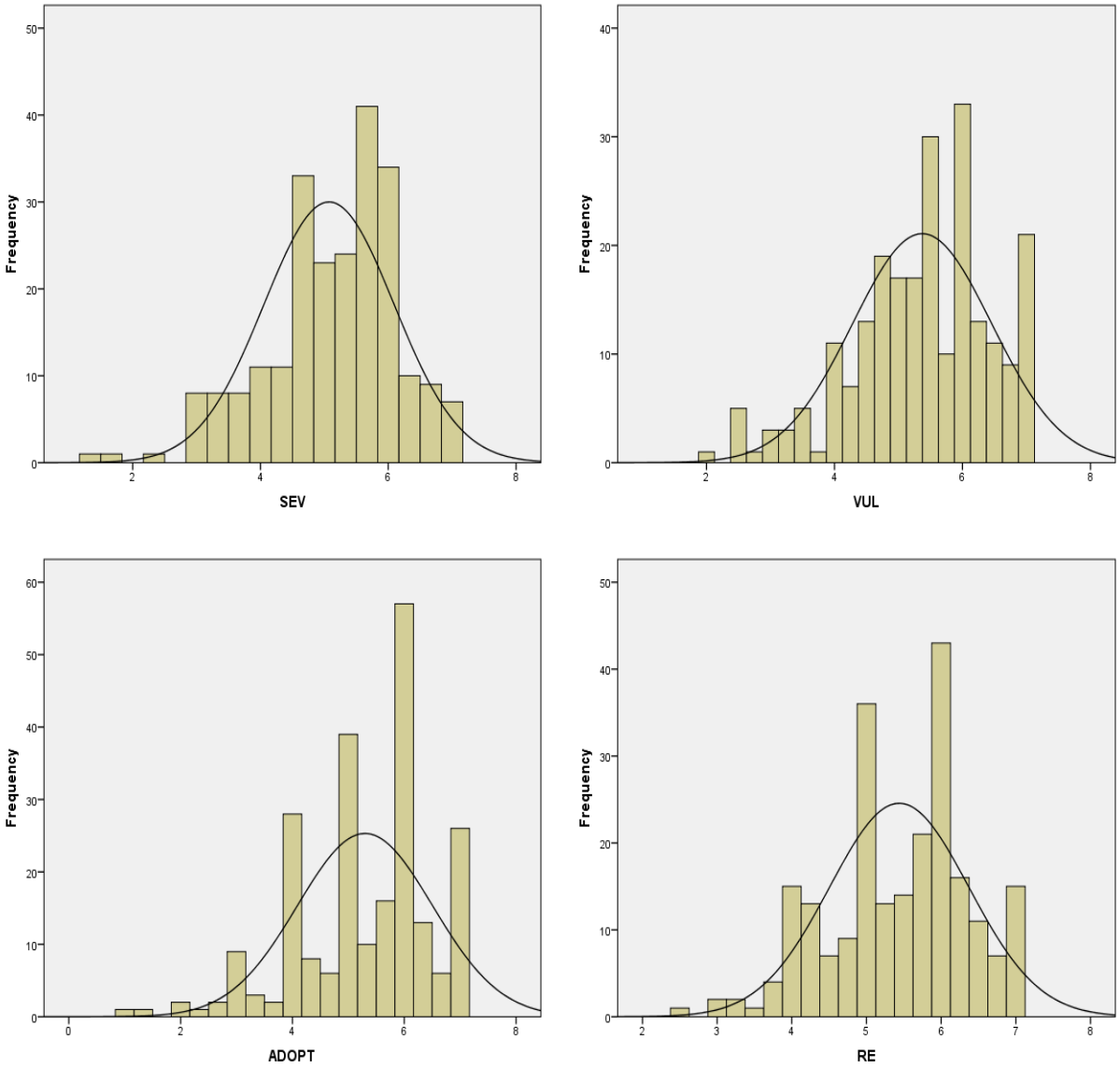
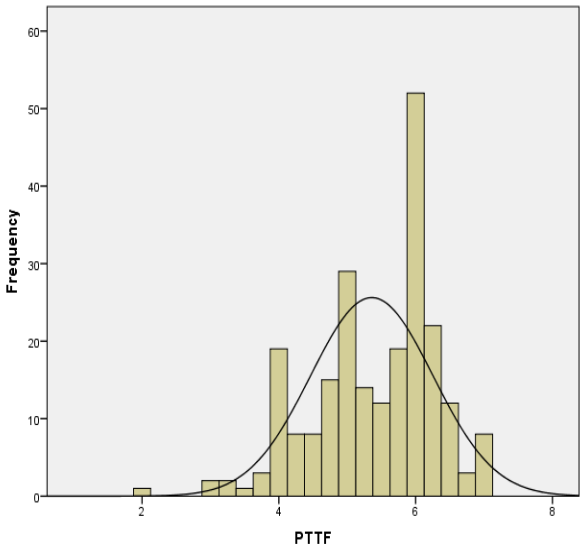
RC1
RC2
RC3
RC4

Appendix K – Composite Histograms

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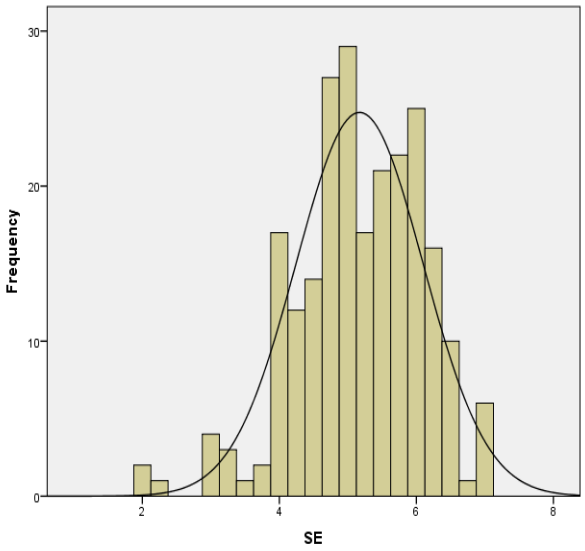
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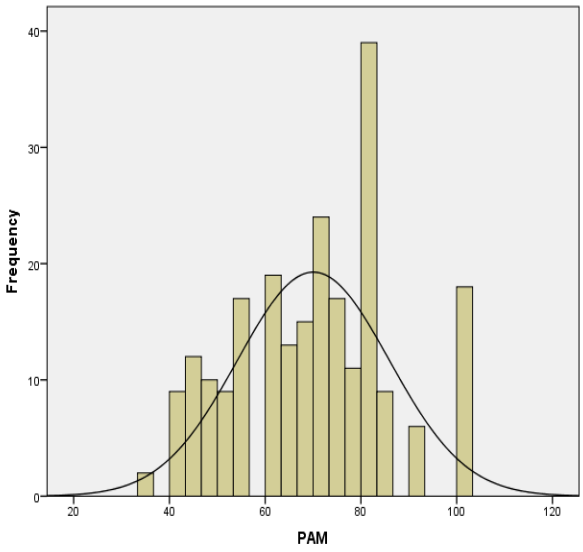
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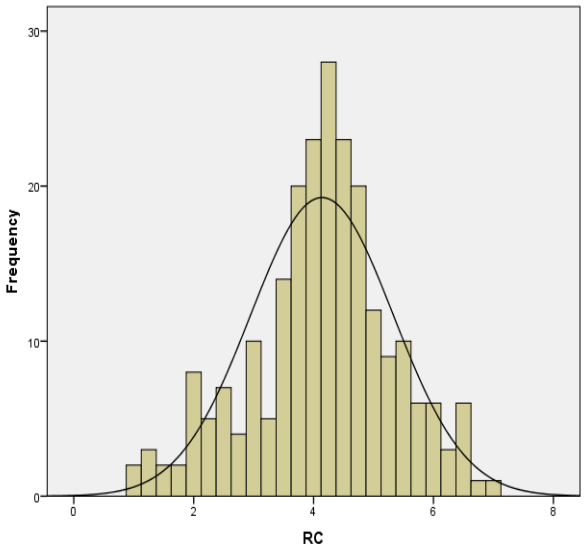
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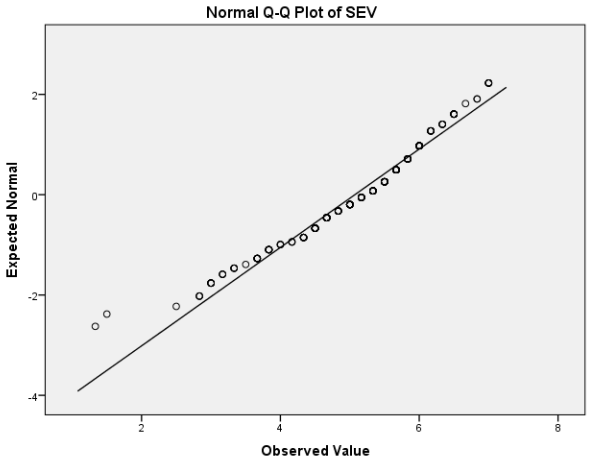
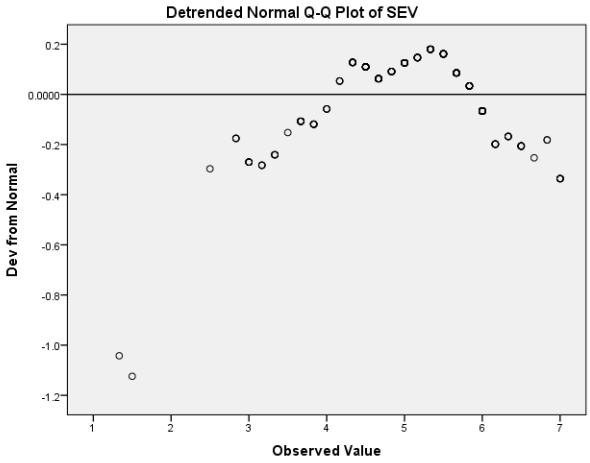
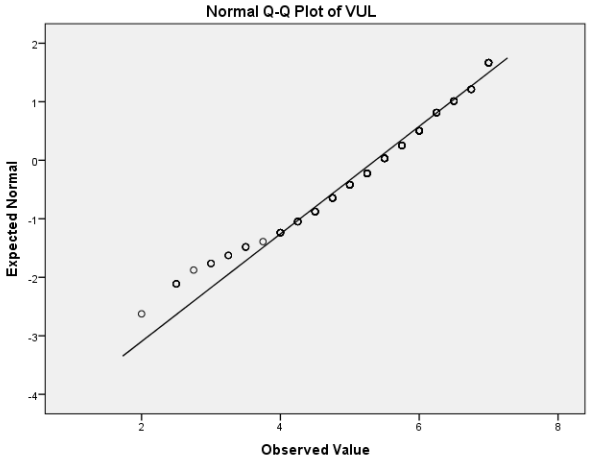
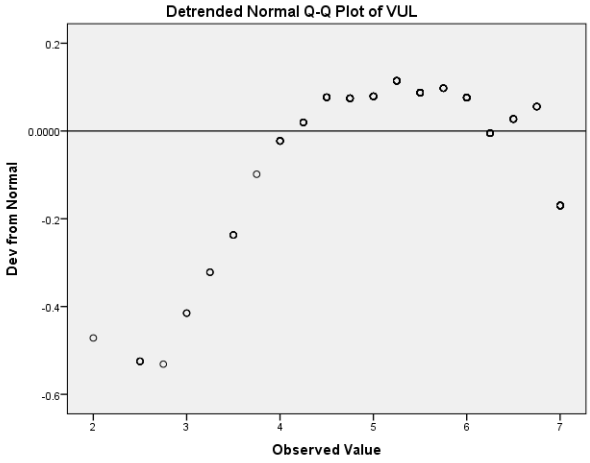
RC

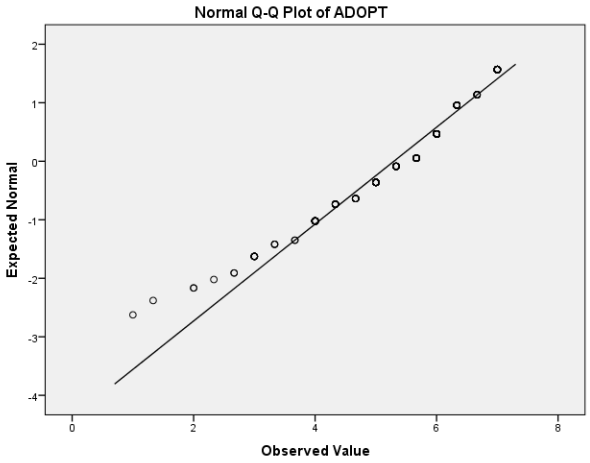
Appendix L – Composite Normality Plots

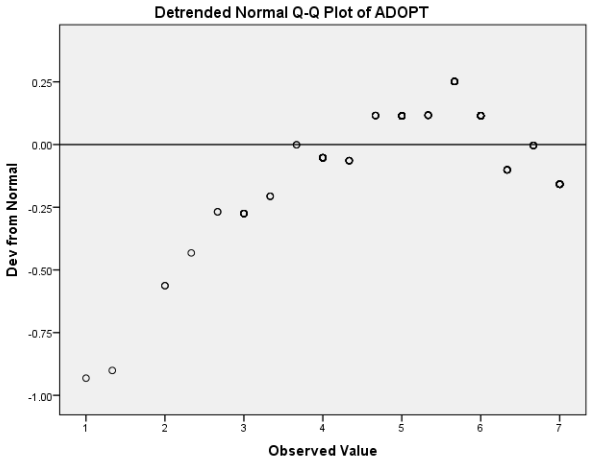


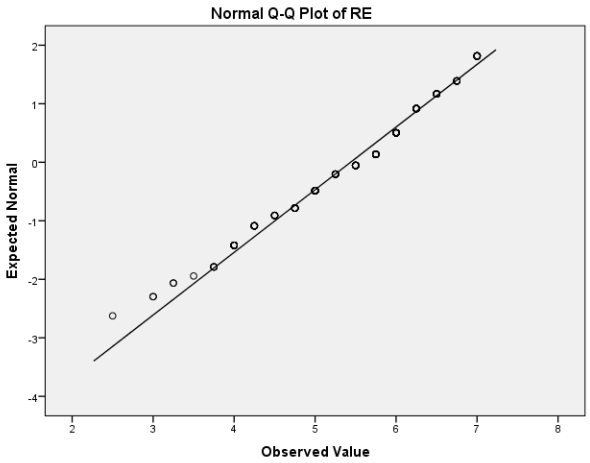


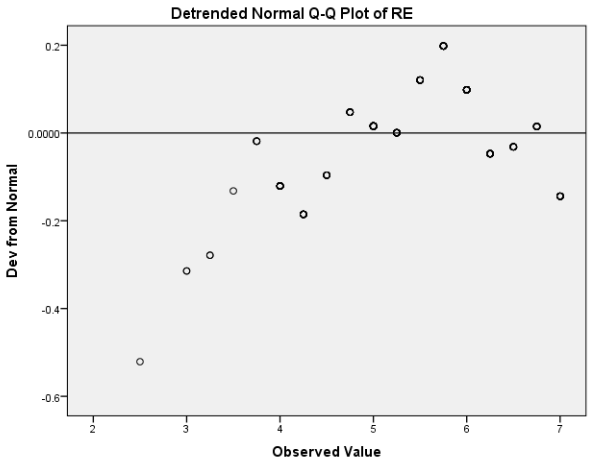


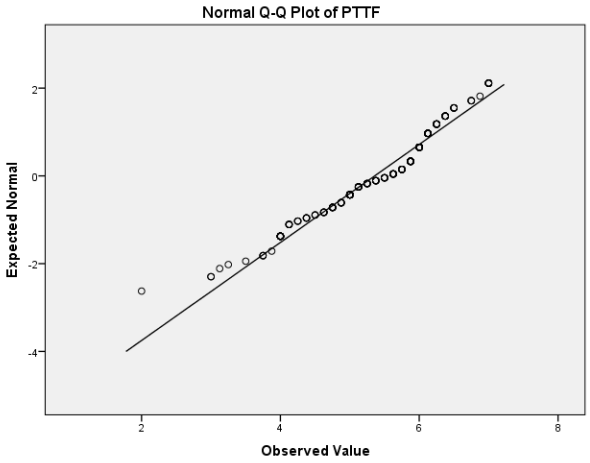


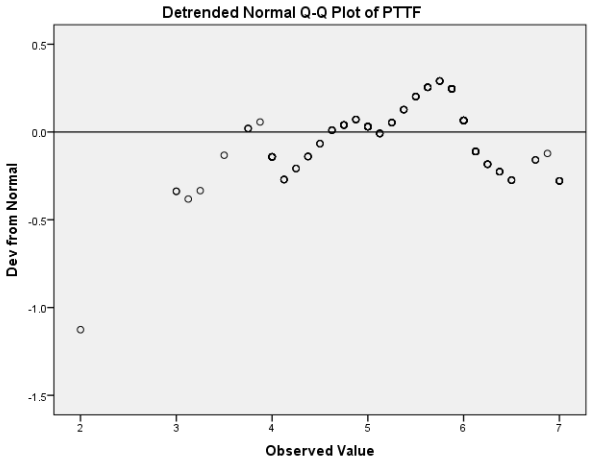


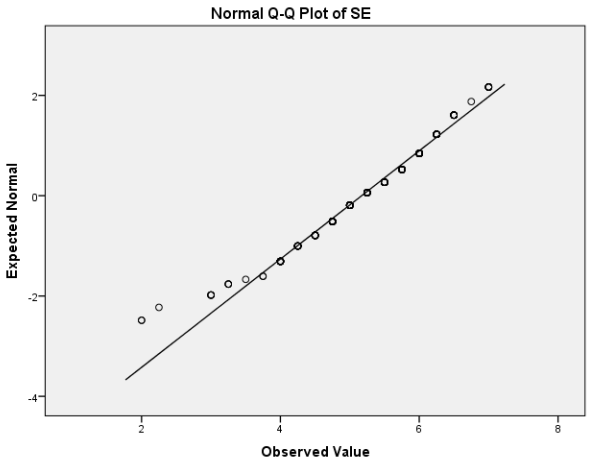


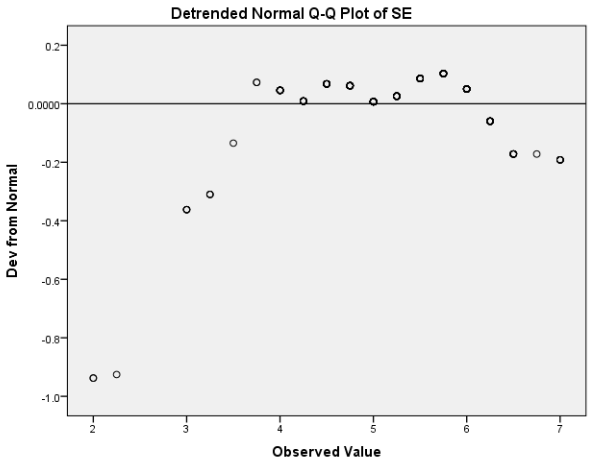

Normal Q-Q Plot of RE
Expected Normal
Observed Value

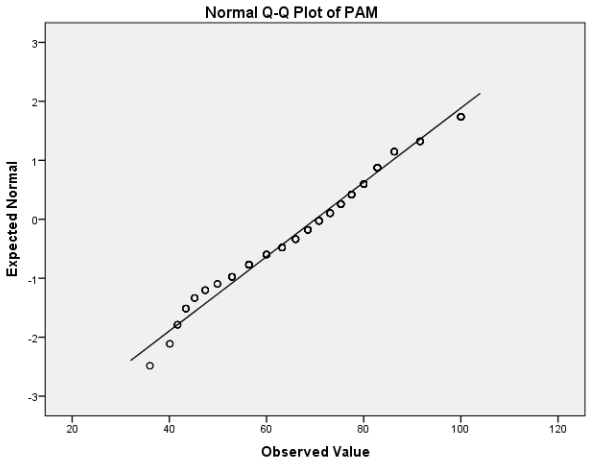

Detrended Normal Q-Q Plot of RE
Dev from Normal
Observed Value

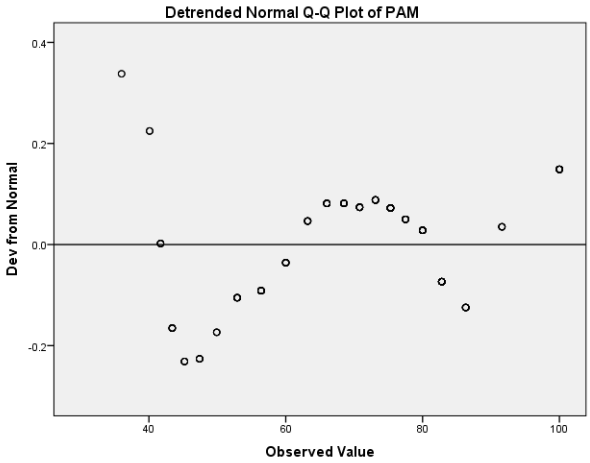

Normal Q-Q Plot of PTTF
Expected Normal
Observed Value

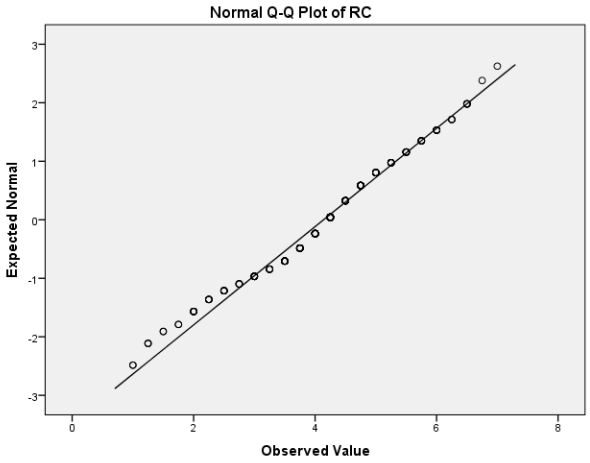

Detrended Normal Q-Q Plot of PTTF
Dev from Normal
Observed Value

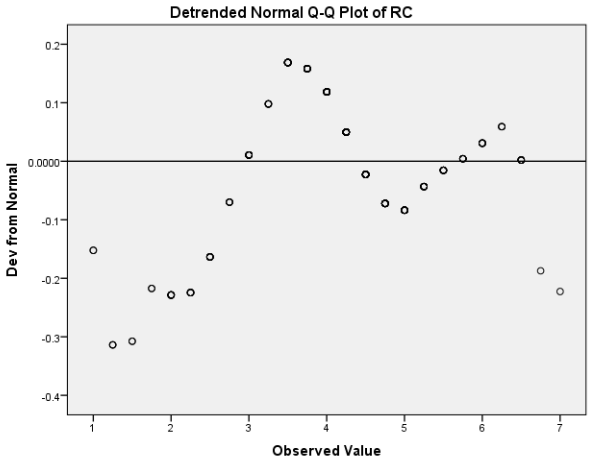

Normal Q-Q Plot of SE
Expected Normal
Observed Value


Detrended Normal Q-Q Plot of SE
Dev from Normal
Observed Value


Normal Q-Q Plot of PAM
Expected Normal
Observed Value

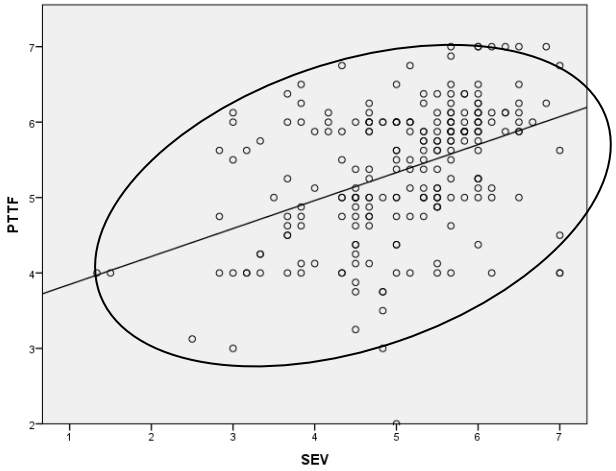

Detrended Normal Q-Q Plot of PAM
Dev from Normal
Observed Value

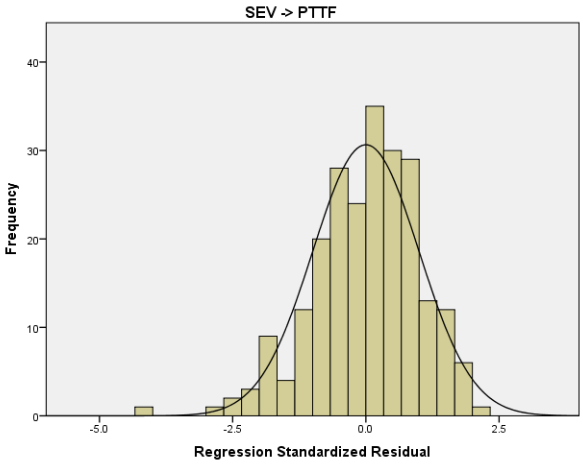

Normal Q-Q Plot of RC
Expected Normal
Observed Value

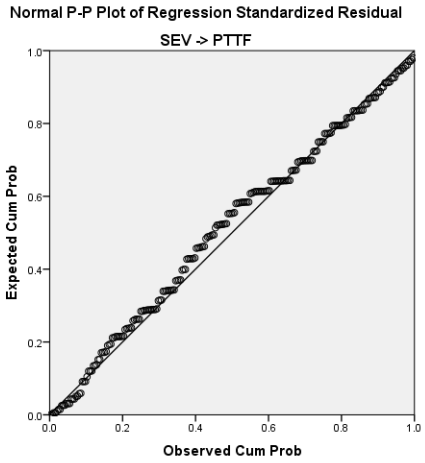

Detrended Normal Q-Q Plot of RC
Dev from Normal
Observed Value

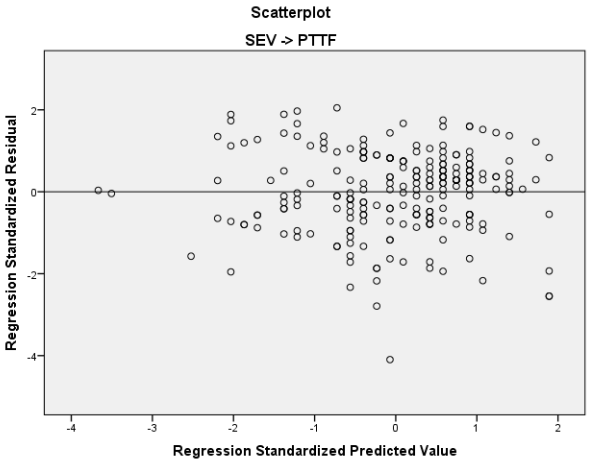
Appendix M – Bivariate Scatterplots and Bivariate Residuals Analysis

SEV → PTTF

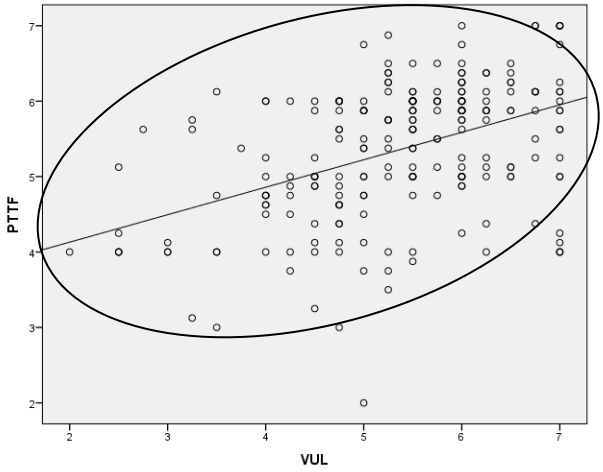


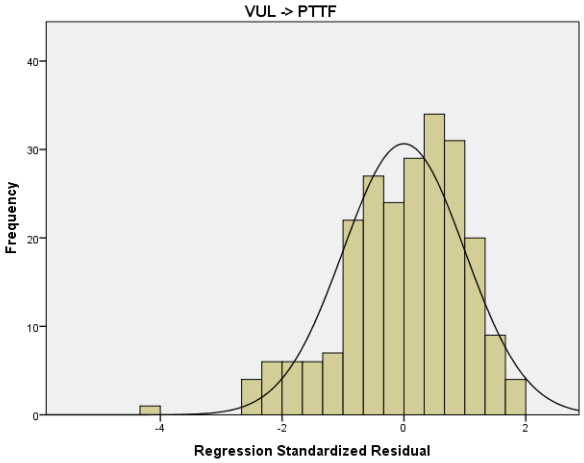


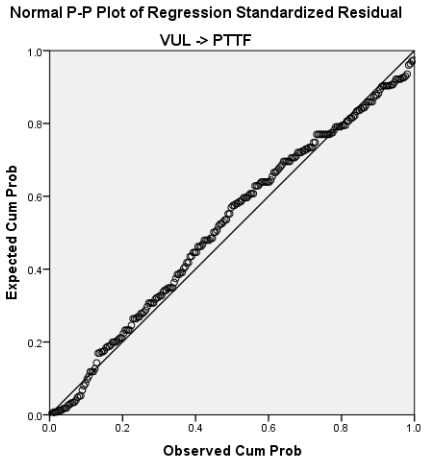


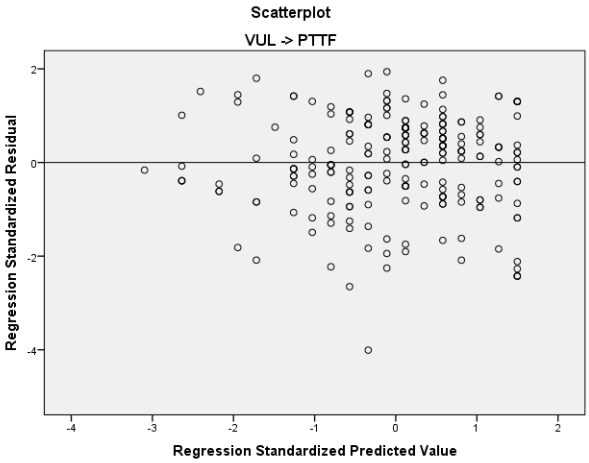


VUL → PTTF

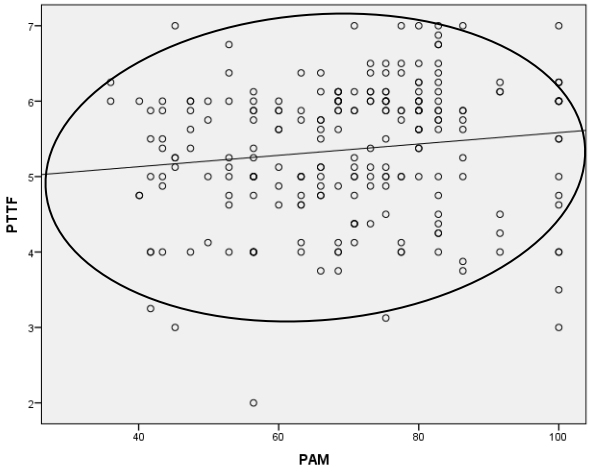

PTTF
VUL

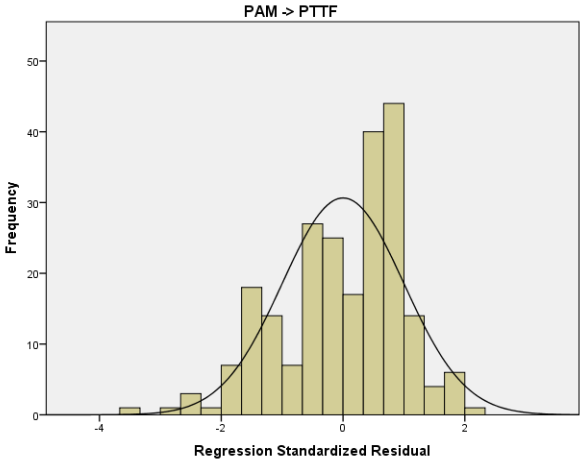

VUL -> PTTF
Frequency
Regression Standardized Residual

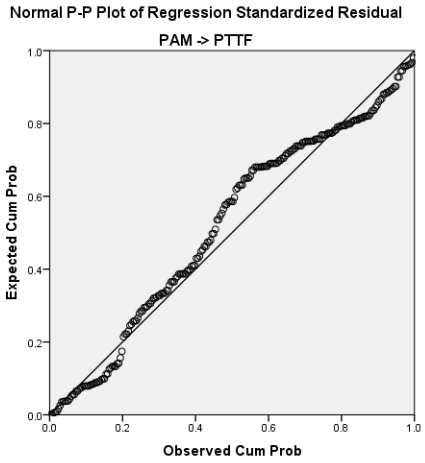

Normal P-P Plot of Regression Standardized Residual
VUL -> PTTF
Expected Cum Prob
Observed Cum Prob

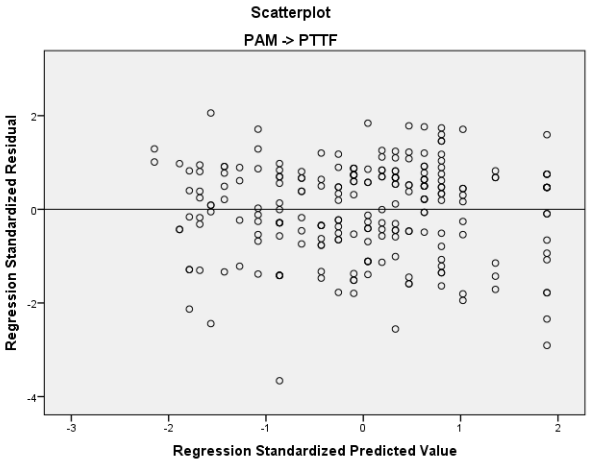

Scatterplot
VUL -> PTTF
Regression Standardized Residual
Regression Standardized Predicted Value

PAM → PTTF

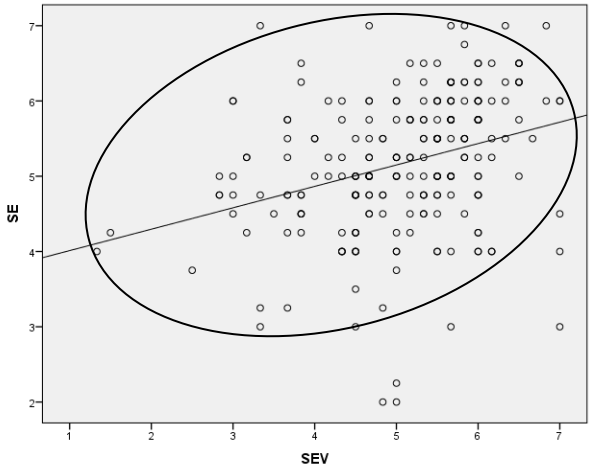

PTTF
PAM

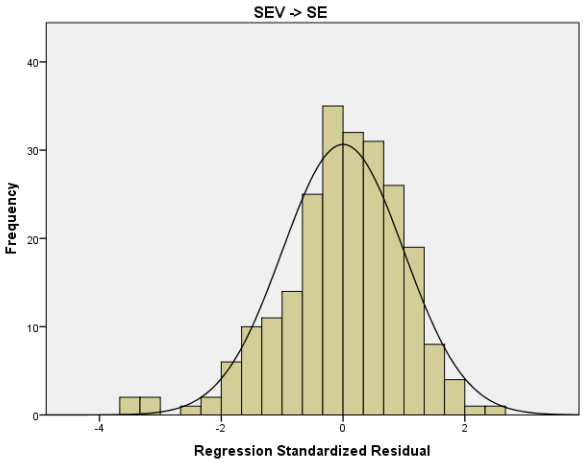

PAM -> PTTF
Frequency
Regression Standardized Residual

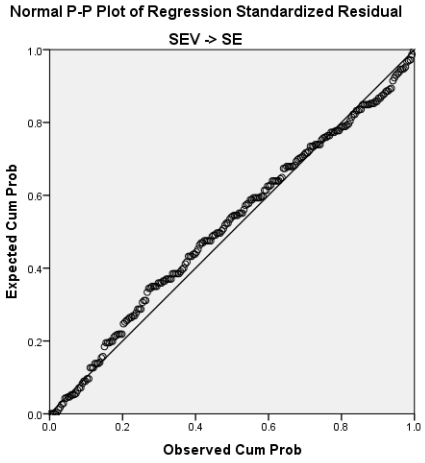

Normal P-P Plot of Regression Standardized Residual
PAM -> PTTF
Expected Cum Prob
Observed Cum Prob

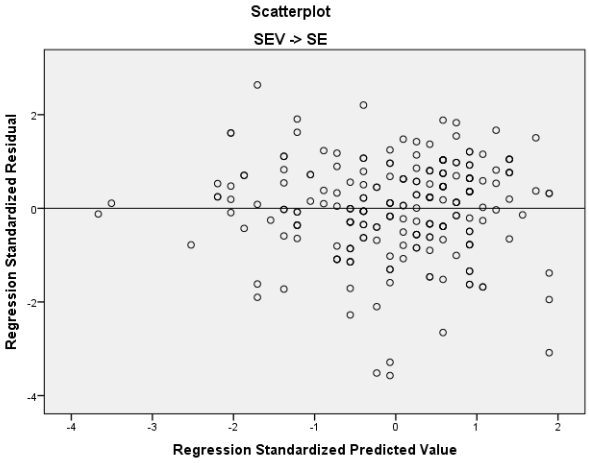

Scatterplot
PAM -> PTTF
Regression Standardized Residual
Regression Standardized Predicted Value

SEV → SE

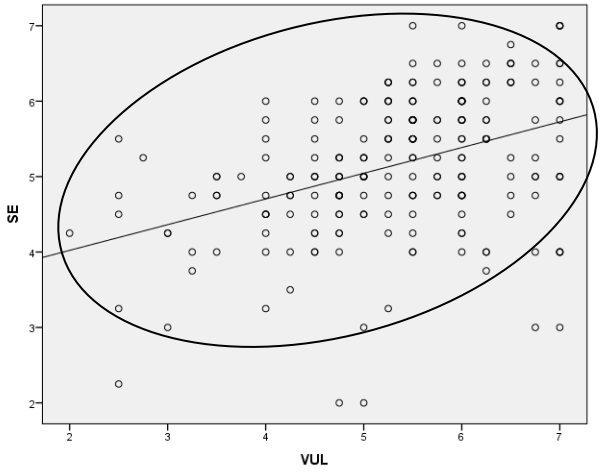

SE
SEV

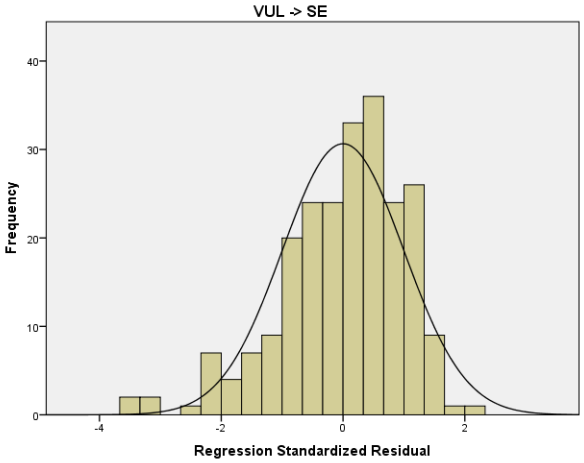

SEV -> SE
Frequency
Regression Standardized Residual

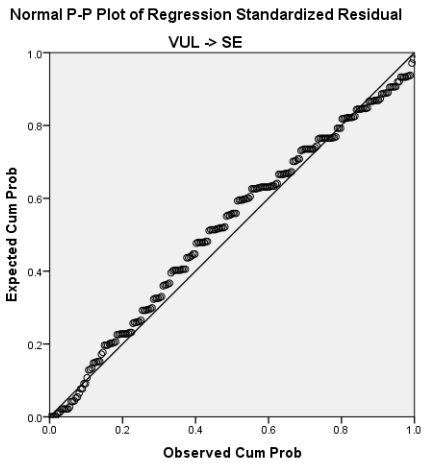

Normal P-P Plot of Regression Standardized Residual
SEV -> SE
Expected Cum Prob
Observed Cum Prob

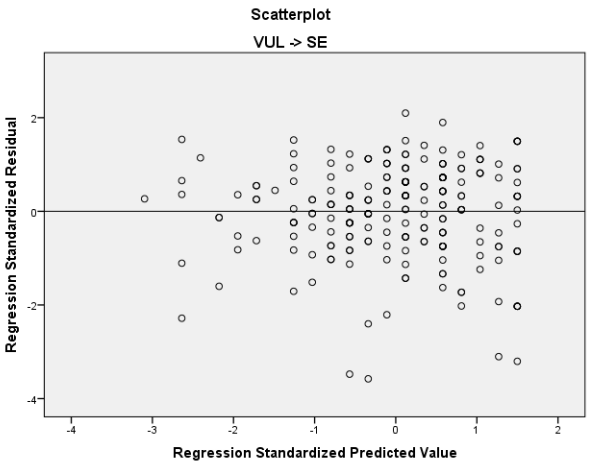

Scatterplot
SEV -> SE
Regression Standardized Residual
Regression Standardized Predicted Value

VUL → SE

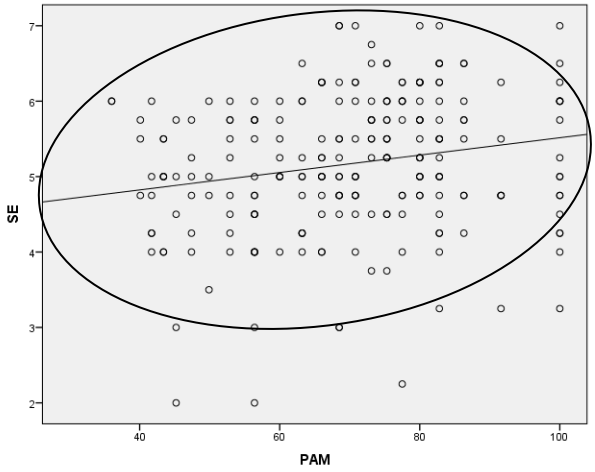

SE
VUL

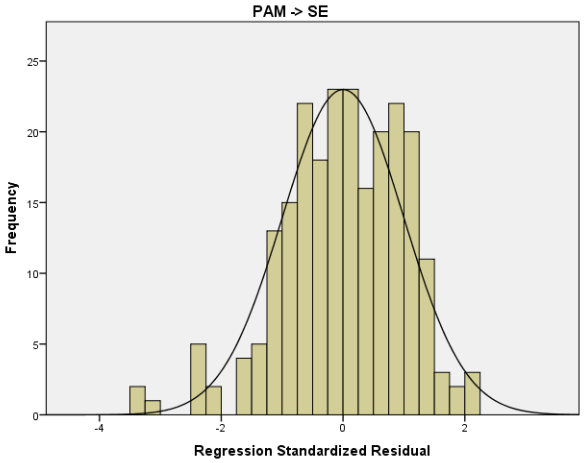

VUL -> SE
Frequency
Regression Standardized Residual

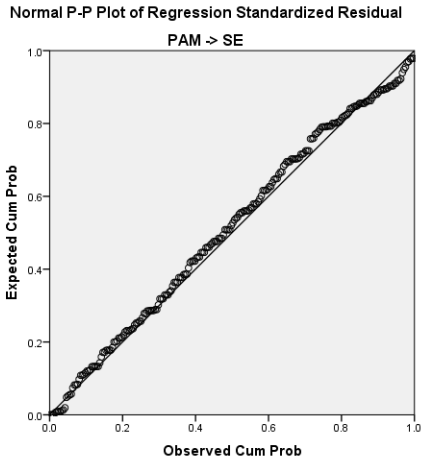

Normal P-P Plot of Regression Standardized Residual
VUL -> SE
Expected Cum Prob
Observed Cum Prob

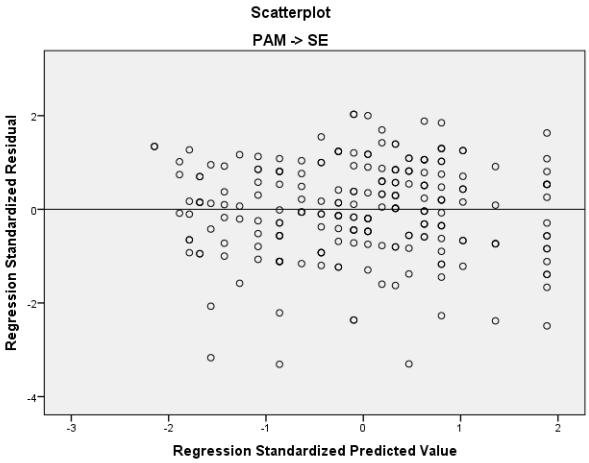

Scatterplot
VUL -> SE
Regression Standardized Residual
Regression Standardized Predicted Value

PAM → SE

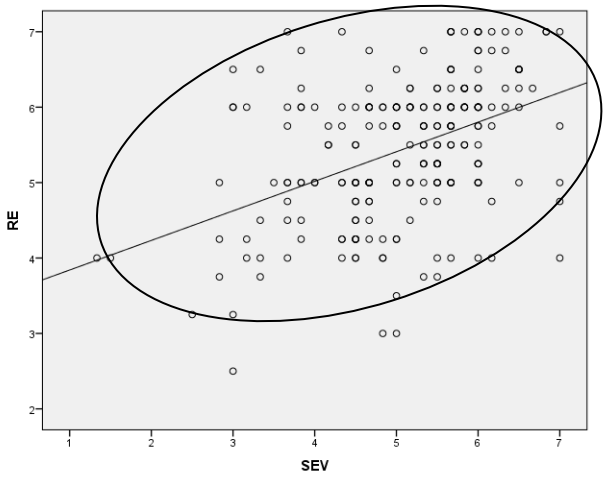

SE
PAM

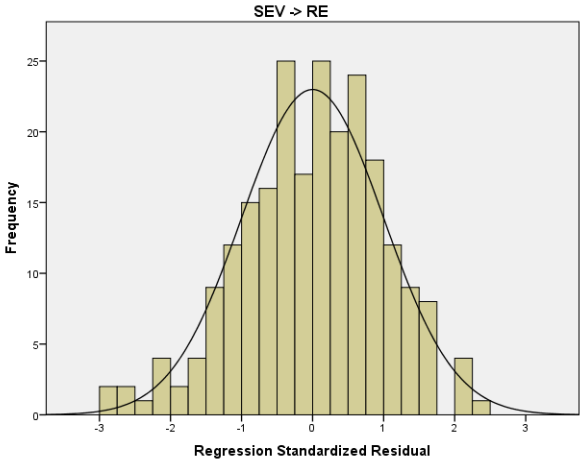

PAM -> SE
Frequency
Regression Standardized Residual

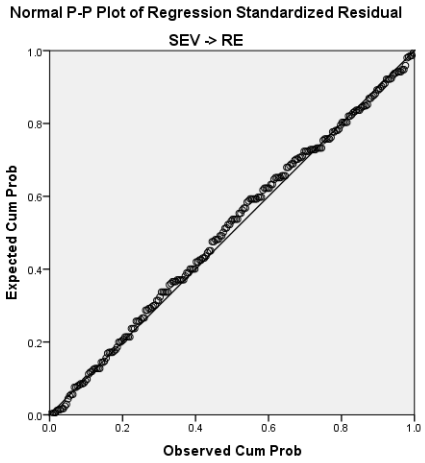

Normal P-P Plot of Regression Standardized Residual
PAM -> SE
Expected Cum Prob
Observed Cum Prob

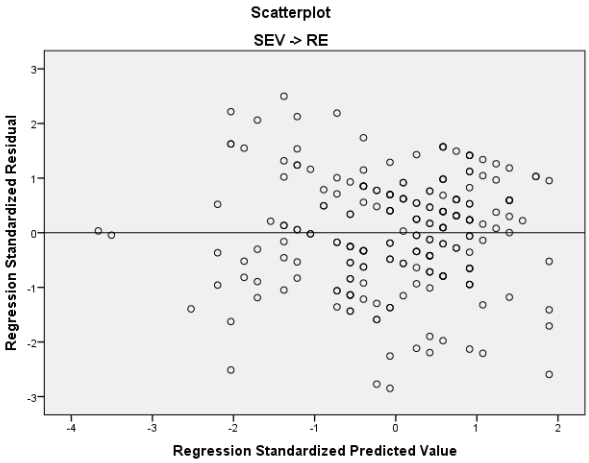

Scatterplot
PAM -> SE
Regression Standardized Residual
Regression Standardized Predicted Value

SEV → RE

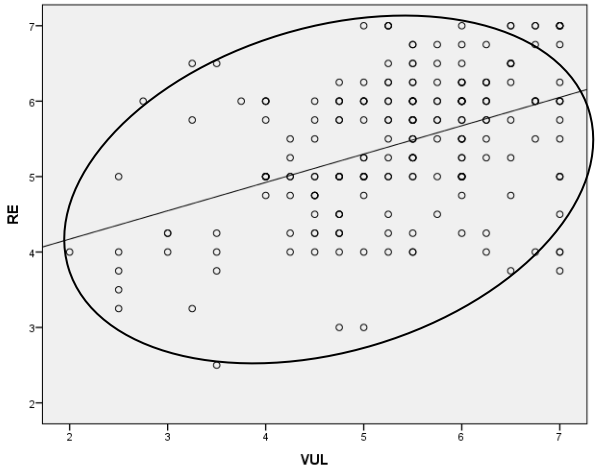

RE
SEV

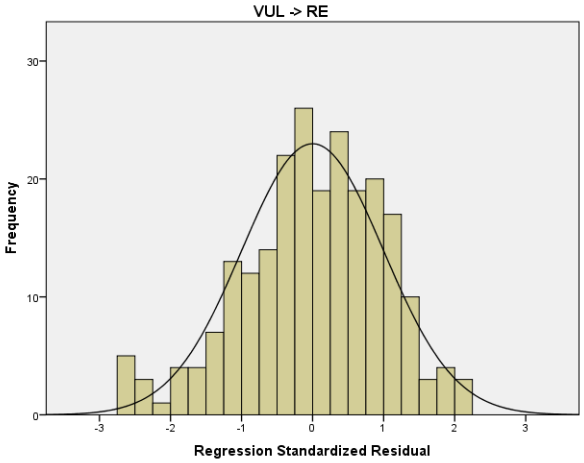

SEV -> RE
Frequency
Regression Standardized Residual

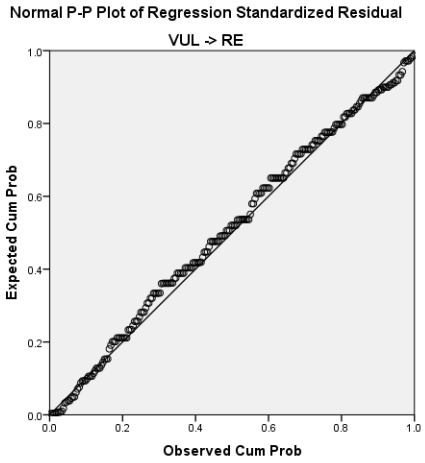

Normal P-P Plot of Regression Standardized Residual
SEV -> RE
Expected Cum Prob
Observed Cum Prob

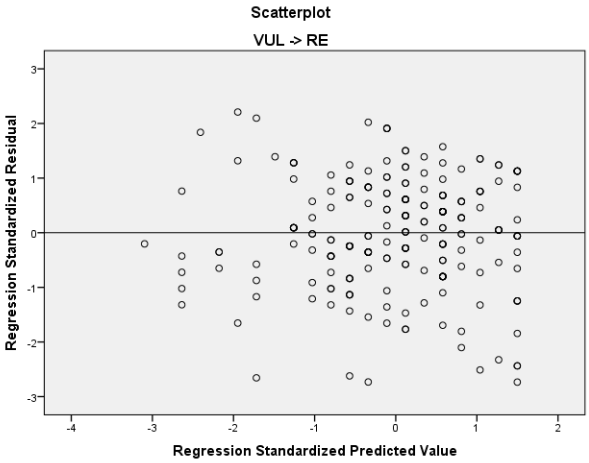

Scatterplot
SEV -> RE
Regression Standardized Residual
Regression Standardized Predicted Value

VUL → RE

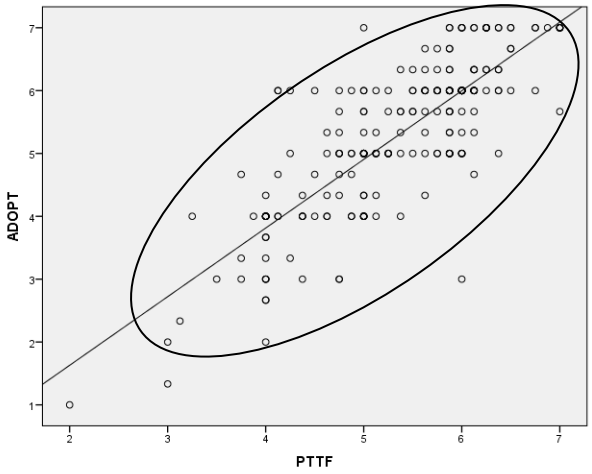

RE
VUL

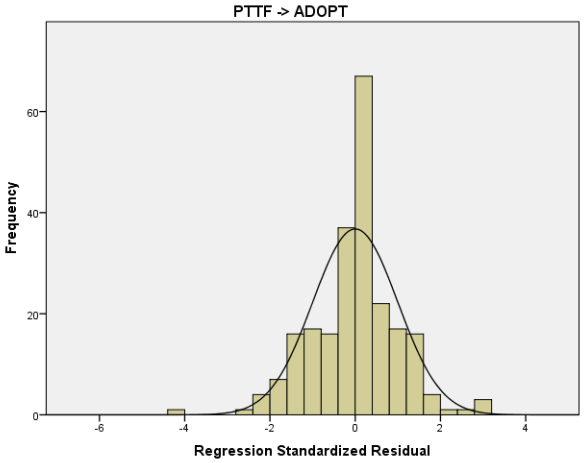

VUL -> RE
Frequency
Regression Standardized Residual

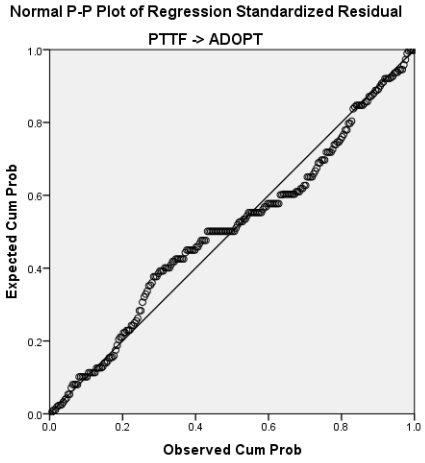

Normal P-P Plot of Regression Standardized Residual
VUL -> RE
Expected Cum Prob
Observed Cum Prob

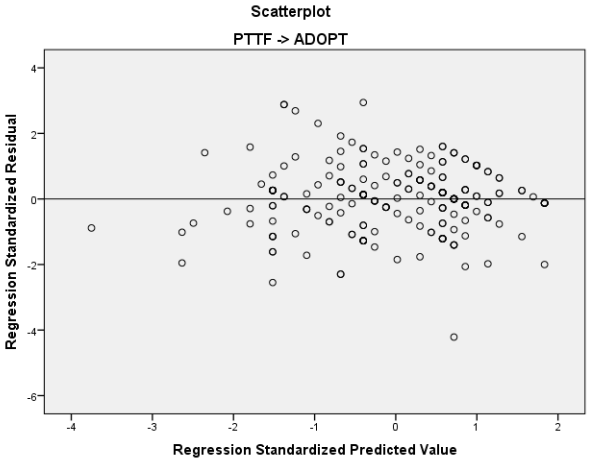

Scatterplot
VUL -> RE
Regression Standardized Residual
Regression Standardized Predicted Value

PTTF → ADOPT

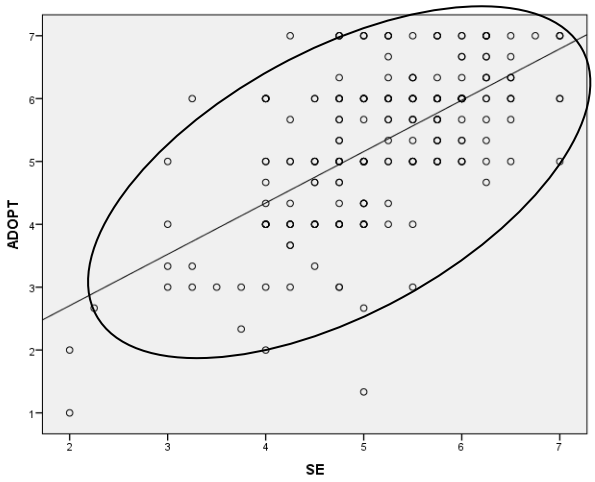

ADOPT
PTTF

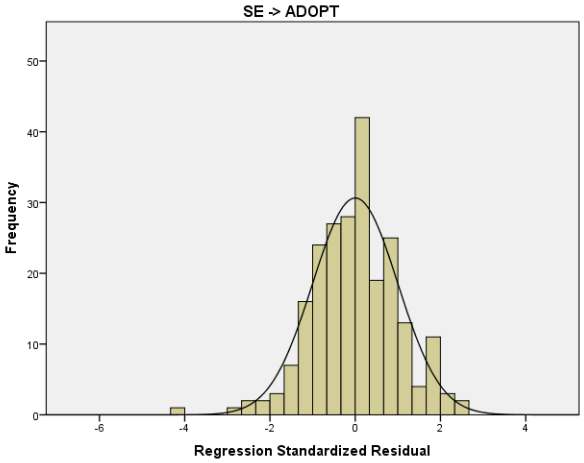

PTTF -> ADOPT
Frequency
Regression Standardized Residual

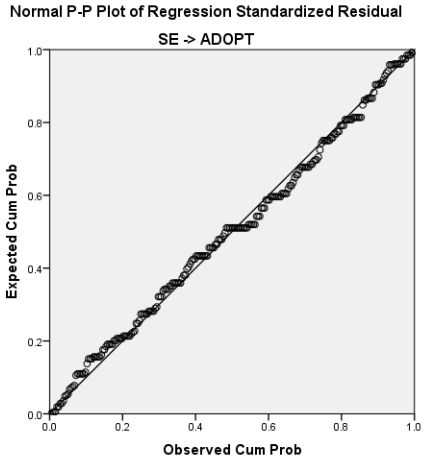

Normal P-P Plot of Regression Standardized Residual
PTTF -> ADOPT
Expected Cum Prob
Observed Cum Prob

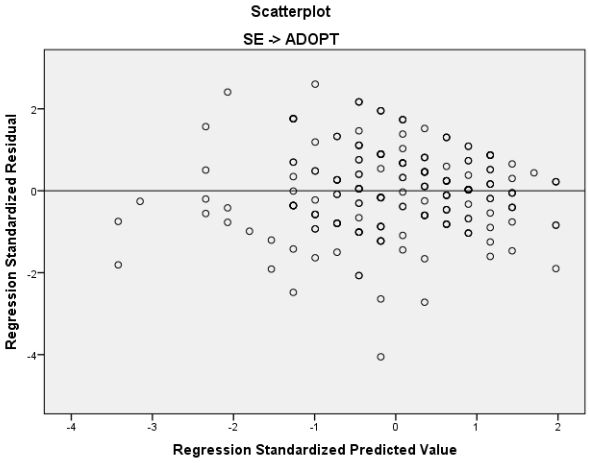

Scatterplot
PTTF -> ADOPT
Regression Standardized Residual
Regression Standardized Predicted Value

SE → ADOPT

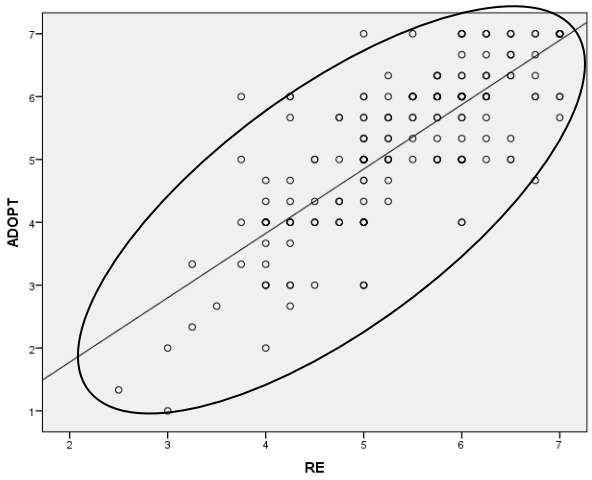

ADOPT
SE

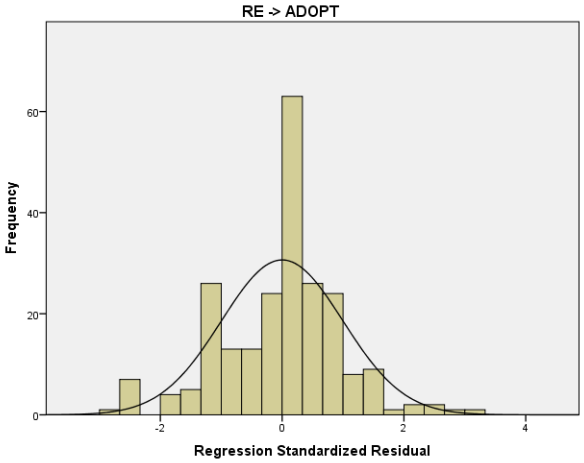

SE -> ADOPT
Frequency
Regression Standardized Residual

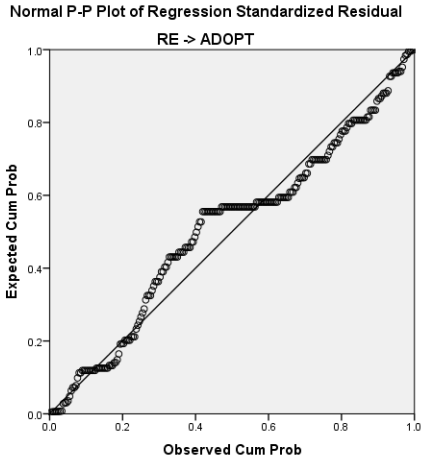

Normal P-P Plot of Regression Standardized Residual
SE -> ADOPT
Expected Cum Prob
Observed Cum Prob

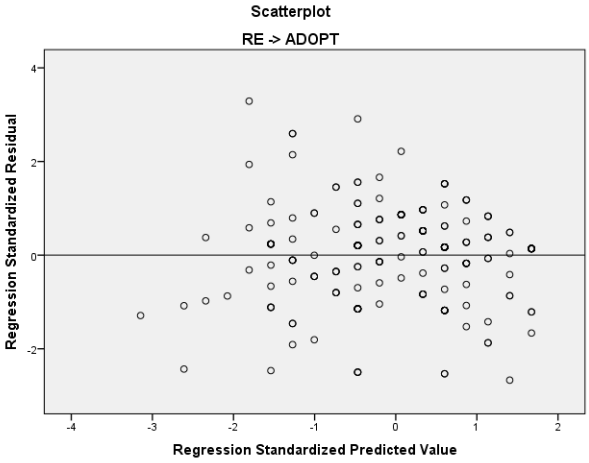

Scatterplot
SE -> ADOPT
Regression Standardized Residual
Regression Standardized Predicted Value

RE → ADOPT

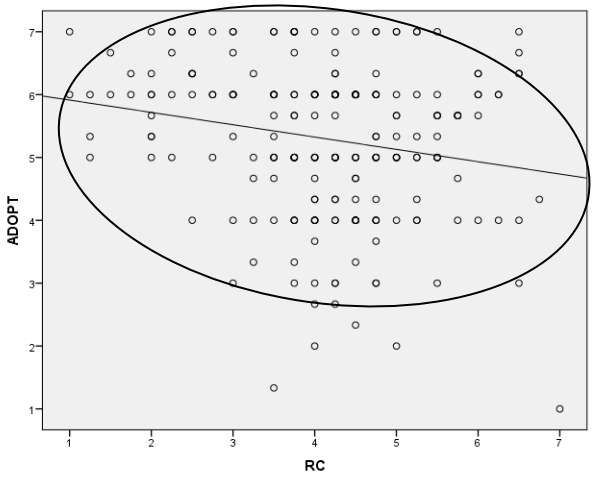

ADOPT
RE

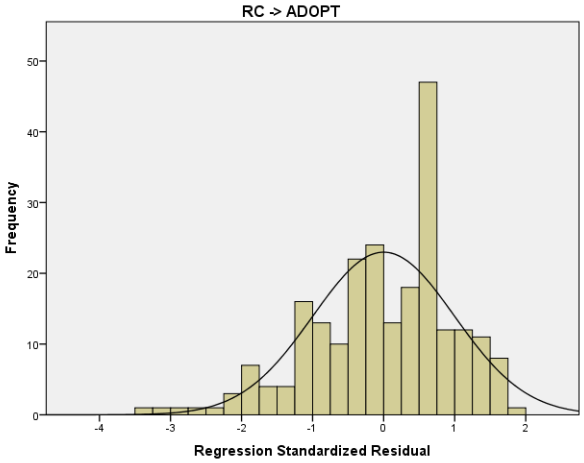

RE -> ADOPT
Frequency
Regression Standardized Residual

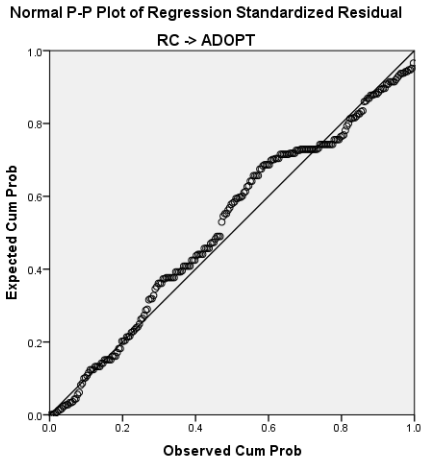

Normal P-P Plot of Regression Standardized Residual
RE -> ADOPT
Expected Cum Prob
Observed Cum Prob

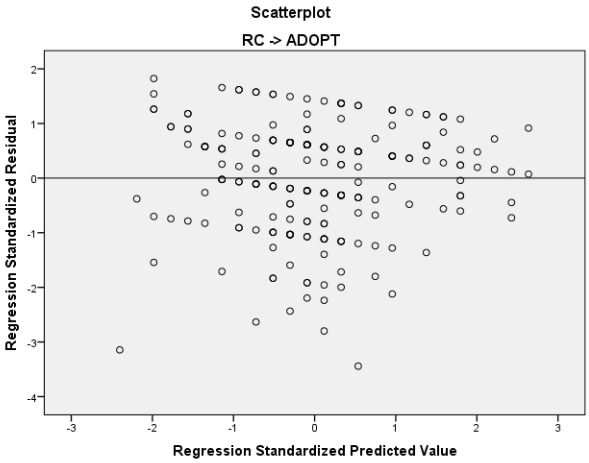

Scatterplot
RE -> ADOPT
Regression Standardized Residual
Regression Standardized Predicted Value

RC → ADOPT

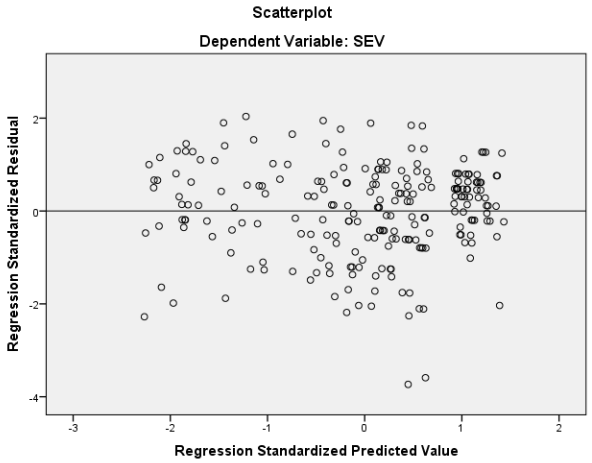

ADOPT
RC

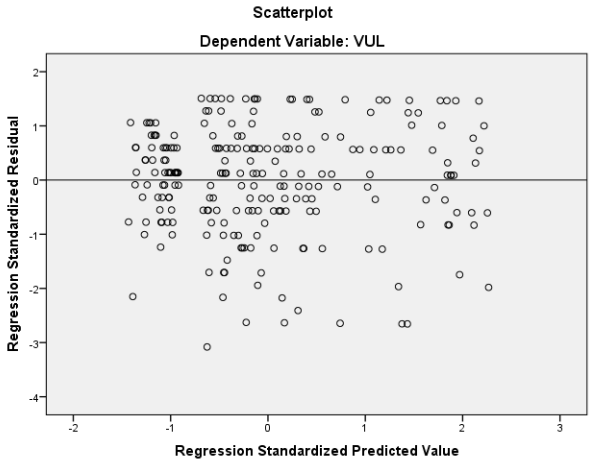

RC -> ADOPT
Frequency
Regression Standardized Residual

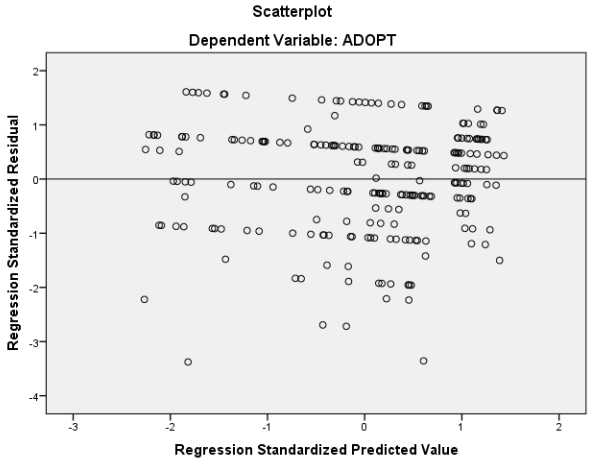

Normal P-P Plot of Regression Standardized Residual
RC -> ADOPT
Expected Cum Prob
Observed Cum Prob

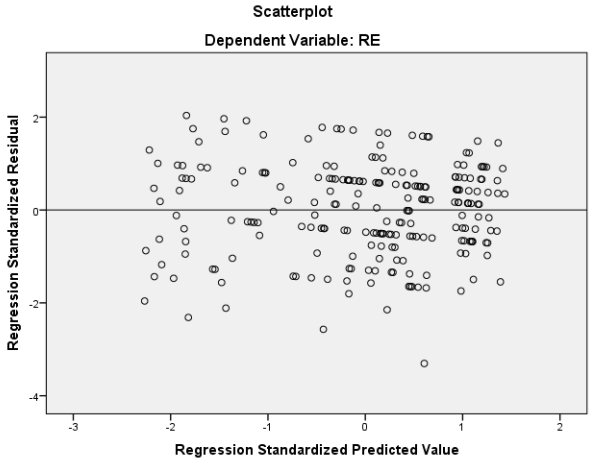

Scatterplot
RC -> ADOPT
Regression Standardized Residual
Regression Standardized Predicted Value

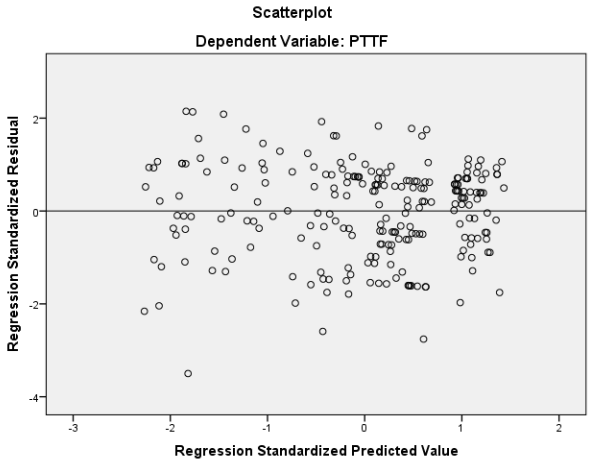
Appendix N – Residual Scatterplot Homoscedasticity Analysis

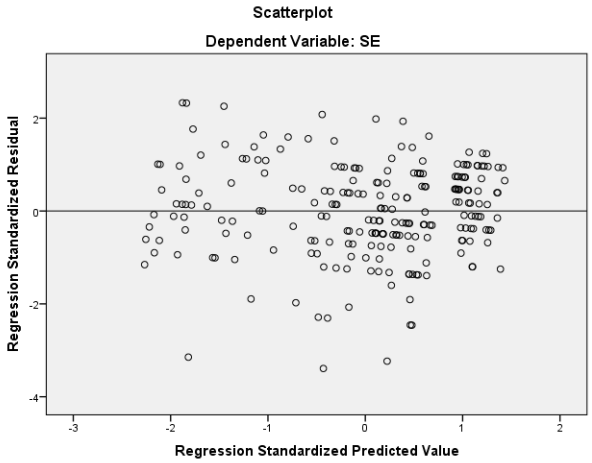


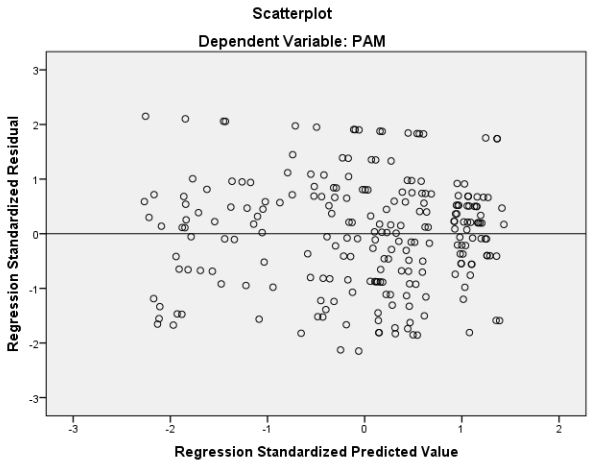


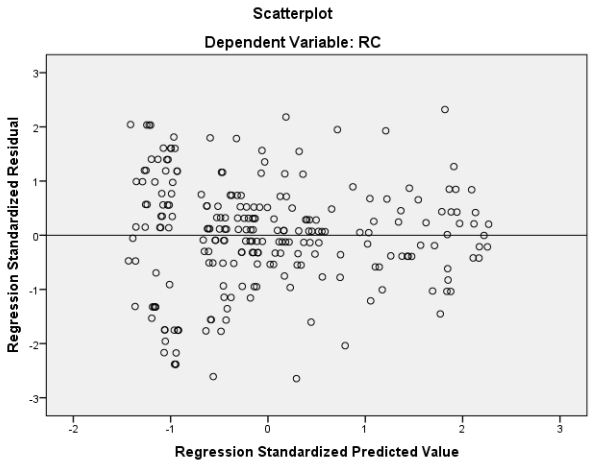









Scatterplot
Dependent Variable: PAM
Regression Standardized Residual
Regression Standardized Predicted Value


Scatterplot
Dependent Variable: RC
Regression Standardized Residual
Regression Standardized Predicted Value

Appendix O – ANOVA Comparison of Groups

Construct/Group		n	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
SEV	1	63	5.06	0.98	0.12	4.81	5.30	3.17	7.00
	2	57	5.27	1.04	0.14	4.99	5.55	1.50	6.83
	3	63	4.93	0.98	0.12	4.68	5.18	1.33	7.00
	4	47	5.05	1.10	0.16	4.73	5.37	2.83	7.00
VUL	1	63	5.34	1.11	0.14	5.06	5.62	2.50	7.00
	2	57	5.50	1.05	0.14	5.22	5.78	2.00	7.00
	3	63	5.34	1.04	0.13	5.08	5.60	2.50	7.00
	4	47	5.29	1.17	0.17	4.95	5.64	2.50	7.00
ADOPT	1	63	5.33	1.10	0.14	5.06	5.61	2.67	7.00
	2	57	5.46	1.19	0.16	5.15	5.78	2.00	7.00
	3	63	5.18	1.22	0.15	4.87	5.49	1.00	7.00
	4	47	5.21	1.36	0.20	4.81	5.60	1.33	7.00
RE	1	63	5.42	0.89	0.11	5.19	5.64	3.50	7.00
	2	**57**	**5.71**	**0.88**	**0.12**	**5.48**	**5.95**	**3.00**	**7.00**
	3	**63**	**5.26**	**0.91**	**0.11**	**5.03**	**5.49**	**3.00**	**7.00**
	4	47	5.37	1.03	0.15	5.07	5.67	2.50	7.00
PTTF	1	63	5.22	0.88	0.11	5.00	5.44	3.33	6.67
	2	**57**	**5.53**	**0.77**	**0.10**	**5.33**	**5.74**	**3.00**	**7.00**
	3	**63**	**5.06**	**0.87**	**0.11**	**4.84**	**5.28**	**2.00**	**6.67**
	4	47	5.35	1.00	0.15	5.06	5.65	3.33	7.00
SE	1	63	5.15	0.98	0.12	4.90	5.39	2.25	6.75
	2	**57**	**5.42**	**0.93**	**0.12**	**5.17**	**5.67**	**2.00**	**7.00**
	3	**63**	**4.96**	**0.87**	**0.11**	**4.74**	**5.18**	**2.00**	**7.00**
	4	47	5.18	0.88	0.13	4.92	5.43	3.00	7.00
PAMSCORE	1	63	68.42	16.23	2.04	64.33	72.51	40.10	100.00
	2	57	71.13	15.00	1.99	67.15	75.11	43.40	100.00
	3	63	69.34	16.55	2.08	65.17	73.51	36.00	100.00
	4	47	71.93	15.71	2.29	67.32	76.54	40.10	100.00
RC	1	63	4.35	1.14	0.14	4.07	4.64	1.25	6.50
	2	57	4.14	1.32	0.17	3.80	4.49	1.25	6.75
	3	63	4.13	0.98	0.12	3.89	4.38	1.00	7.00
	4	47	3.85	1.33	0.19	3.46	4.24	1.00	6.50

Dependent Variable	(I) GROUP	(J) GROUP	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
SEV	1	2	-0.213	0.186	0.661	-0.695	0.268
		3	0.127	0.181	0.897	-0.343	0.597
		4	0.006	0.196	1.000	-0.502	0.514
	2	1	0.213	0.186	0.661	-0.268	0.695
		3	0.340	0.186	0.263	-0.141	0.822
		4	0.219	0.201	0.694	-0.300	0.739
	3	1	-0.127	0.181	0.897	-0.597	0.343
		2	-0.340	0.186	0.263	-0.822	0.141
		4	-0.121	0.196	0.927	-0.629	0.387
	4	1	-0.006	0.196	1.000	-0.514	0.502
		2	-0.219	0.201	0.694	-0.739	0.300
		3	0.121	0.196	0.927	-0.387	0.629
VUL	1	2	-0.163	0.200	0.847	-0.680	0.354
		3	-0.004	0.195	1.000	-0.508	0.500
		4	0.045	0.211	0.997	-0.500	0.590
	2	1	0.163	0.200	0.847	-0.354	0.680
		3	0.159	0.200	0.857	-0.358	0.676
		4	0.207	0.215	0.770	-0.350	0.765
	3	1	0.004	0.195	1.000	-0.500	0.508
		2	-0.159	0.200	0.857	-0.676	0.358
		4	0.049	0.211	0.996	-0.496	0.594
	4	1	-0.045	0.211	0.997	-0.590	0.500
		2	-0.207	0.215	0.770	-0.765	0.350
		3	-0.049	0.211	0.996	-0.594	0.496
ADOPT	1	2	-0.129	0.221	0.938	-0.702	0.444
		3	0.153	0.216	0.893	-0.405	0.712
		4	0.128	0.233	0.947	-0.476	0.732
	2	1	0.129	0.221	0.938	-0.444	0.702
		3	0.282	0.221	0.580	-0.291	0.855
		4	0.256	0.239	0.706	-0.361	0.874
	3	1	-0.153	0.216	0.893	-0.712	0.405
		2	-0.282	0.221	0.580	-0.855	0.291
		4	-0.026	0.233	1.000	-0.630	0.578
	4	1	-0.128	0.233	0.947	-0.732	0.476
		2	-0.256	0.239	0.706	-0.874	0.361
		3	0.026	0.233	1.000	-0.578	0.630

RE	1	2	-0.298	0.169	0.293	-0.736	0.139
		3	0.159	0.165	0.770	-0.268	0.585
		4	0.044	0.178	0.995	-0.417	0.505
	2	1	0.298	0.169	0.293	-0.139	0.736
		3	**0.457***	0.169	0.037	0.020	0.894
		4	0.343	0.182	0.239	-0.129	0.814
	3	1	-0.159	0.165	0.770	-0.585	0.268
		2	**-0.457***	0.169	0.037	-0.894	-0.020
		4	-0.114	0.178	0.918	-0.576	0.347
	4	1	-0.044	0.178	0.995	-0.505	0.417
		2	-0.343	0.182	0.239	-0.814	0.129
		3	0.114	0.178	0.918	-0.347	0.576
PTTF	1	2	-0.310	0.160	0.217	-0.725	0.105
		3	0.164	0.156	0.721	-0.241	0.569
		4	-0.132	0.169	0.862	-0.570	0.305
	2	1	0.310	0.160	0.217	-0.105	0.725
		3	**0.474***	0.160	0.018	0.059	0.889
		4	0.178	0.173	0.734	-0.270	0.625
	3	1	-0.164	0.156	0.721	-0.569	0.241
		2	**-0.474***	0.160	0.018	-0.889	-0.059
		4	-0.296	0.169	0.299	-0.734	0.141
	4	1	0.132	0.169	0.862	-0.305	0.570
		2	-0.178	0.173	0.734	-0.625	0.270
		3	0.296	0.169	0.299	-0.141	0.734
SE	1	2	-0.274	0.168	0.361	-0.708	0.160
		3	0.183	0.164	0.680	-0.241	0.606
		4	-0.029	0.177	0.998	-0.487	0.429
	2	1	0.274	0.168	0.361	-0.160	0.708
		3	**0.457***	0.168	0.035	0.023	0.891
		4	0.246	0.181	0.527	-0.223	0.714
	3	1	-0.183	0.164	0.680	-0.606	0.241
		2	**-0.457***	0.168	0.035	-0.891	-0.023
		4	-0.211	0.177	0.631	-0.669	0.247
	4	1	0.029	0.177	0.998	-0.429	0.487
		2	-0.246	0.181	0.527	-0.714	0.223
		3	0.211	0.177	0.631	-0.247	0.669

PAMSCORE	1	2	-2.714	2.909	0.787	-10.244	4.816
		3	-0.919	2.836	0.988	-8.258	6.420
		4	-3.513	3.067	0.662	-11.452	4.427
	2	1	2.714	2.909	0.787	-4.816	10.244
		3	1.795	2.909	0.927	-5.735	9.325
		4	-0.799	3.136	0.994	-8.915	7.317
	3	1	0.919	2.836	0.988	-6.420	8.258
		2	-1.795	2.909	0.927	-9.325	5.735
		4	-2.594	3.067	0.833	-10.533	5.346
	4	1	3.513	3.067	0.662	-4.427	11.452
		2	0.799	3.136	0.994	-7.317	8.915
		3	2.594	3.067	0.833	-5.346	10.533
RC	1	2	0.208	0.217	0.771	-0.353	0.770
		3	0.218	0.211	0.730	-0.329	0.765
		4	0.502	0.229	0.127	-0.090	1.094
	2	1	-0.208	0.217	0.771	-0.770	0.353
		3	0.010	0.217	1.000	-0.551	0.571
		4	0.294	0.234	0.591	-0.311	0.899
	3	1	-0.218	0.211	0.730	-0.765	0.329
		2	-0.010	0.217	1.000	-0.571	0.551
		4	0.284	0.229	0.601	-0.308	0.876
	4	1	-0.502	0.229	0.127	-1.094	0.090
		2	-0.294	0.234	0.591	-0.899	0.311
		3	-0.284	0.229	0.601	-0.876	0.308

**** The mean difference is significant at the 0.05 level.***

Appendix P – ANOVA and MANOVA Control Variable Analysis

Age

Construct	Age	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	18-49	69	5.430	5.250	5.610	21.809	7.27	7.599	**0.000**
	50-59	56	5.188	4.904	5.471				
	60-69	54	4.941	4.640	5.242				
	70+	51	4.601	4.315	4.888				
	Total	230	5.072	4.940	5.205				
VUL	18-49	69	5.540	5.323	5.757	15.895	5.298	4.692	**0.003**
	50-59	56	5.683	5.412	5.954				
	60-69	54	5.134	4.805	5.464				
	70+	51	5.044	4.721	5.368				
	Total	230	5.370	5.228	5.511				
ADOPT	18-49	69	5.696	5.482	5.909	30.757	10.252	7.635	**0.000**
	50-59	56	5.536	5.204	5.867				
	60-69	54	4.988	4.627	5.348				
	70+	51	4.824	4.483	5.164				
	Total	230	5.297	5.140	5.454				
RE	18-49	69	5.696	5.515	5.877	21.121	7.04	8.911	**0.000**
	50-59	56	5.670	5.429	5.910				
	60-69	54	5.347	5.085	5.609				
	70+	51	4.931	4.659	5.204				
	Total	230	5.438	5.317	5.559				
PTTF	18-49	69	5.541	5.371	5.712	15.753	5.251	7.175	**0.000**
	50-59	56	5.446	5.187	5.706				
	60-69	54	5.173	4.942	5.404				
	70+	51	4.863	4.606	5.119				
	Total	230	5.281	5.166	5.397				
SE	18-49	69	5.482	5.296	5.668	13.283	4.428	5.458	**0.001**
	50-59	56	5.246	4.990	5.501				
	60-69	54	4.917	4.639	5.194				
	70+	51	4.936	4.692	5.181				
	Total	230	5.171	5.050	5.291				
PAM	18-49	69	71.229	67.986	74.472	540.351	180.117	0.712	0.545
	50-59	56	68.363	63.849	72.876				
	60-69	54	71.794	67.460	76.129				
	70+	51	68.512	63.519	73.504				
	Total	230	70.061	67.999	72.123				
RC	18-49	69	4.232	3.886	4.578	5.476	1.825	1.292	0.278
	50-59	56	3.875	3.520	4.230				
	60-69	54	4.167	3.882	4.452				
	70+	51	4.275	4.081	4.468				
	Total	230	4.139	3.984	4.294				

Multiple Comparisons (Tukey's HSD)

Dependent Variable	(I) AGE	(J) AGE	Mean Difference (I-J)	Std. Error	Sig.
SEV	18-49	50-59	.242	.176	.514
		60-69	**.489***	**.178**	**.032**
		70+	**.829***	**.181**	**.000**
	50-59	18-49	-.242	.176	.514
		60-69	.246	.187	.551
		70+	**.586***	**.189**	**.012**
	60-69	18-49	**-.489***	**.178**	**.032**
		50-59	-.246	.187	.551
		70+	.340	.191	.285
	70+	18-49	**-.829***	**.181**	**.000**
		50-59	**-.586***	**.189**	**.012**
		60-69	-.340	.191	.285
VUL	18-49	50-59	-.143	.191	.877
		60-69	.406	.193	.156
		70+	.496	.196	.059
	50-59	18-49	.143	.191	.877
		60-69	**.549***	**.203**	**.036**
		70+	**.639***	**.206**	**.011**
	60-69	18-49	-.406	.193	.156
		50-59	**-.549***	**.203**	**.036**
		70+	.090	.207	.972
	70+	18-49	-.496	.196	.059
		50-59	**-.639***	**.206**	**.011**
		60-69	-.090	.207	.972
ADOPT	18-49	50-59	.160	.208	.869
		60-69	**.708***	**.211**	**.005**
		70+	**.872***	**.214**	**.000**
	50-59	18-49	-.160	.208	.869
		60-69	.548	.221	.066
		70+	**.712***	**.224**	**.009**
	60-69	18-49	**-.708***	**.211**	**.005**
		50-59	-.548	.221	.066
		70+	.164	.226	.887
	70+	18-49	**-.872***	**.214**	**.000**
		50-59	**-.712***	**.224**	**.009**
		60-69	-.164	.226	.887

RE	18-49	50-59	.026	.160	.998
		60-69	.348	.162	.138
		70+	**.764***	**.164**	**.000**
	50-59	18-49	-.026	.160	.998
		60-69	.322	.170	.230
		70+	**.738***	**.172**	**.000**
	60-69	18-49	-.348	.162	.138
		50-59	-.322	.170	.230
		70+	.416	.174	.081
	70+	18-49	**-.764***	**.164**	**.000**
		50-59	**-.738***	**.172**	**.000**
		60-69	-.416	.174	.081
SE	18-49	50-59	.236	.162	.464
		60-69	**.565***	**.164**	**.004**
		70+	**.546***	**.166**	**.007**
	50-59	18-49	-.236	.162	.464
		60-69	.329	.172	.225
		70+	.309	.174	.289
	60-69	18-49	**-.565***	**.164**	**.004**
		50-59	-.329	.172	.225
		70+	-.020	.176	1.000
	70+	18-49	**-.546***	**.166**	**.007**
		50-59	-.309	.174	.289
		60-69	.020	.176	1.000
PTTF	18-49	50-59	.0945	.154	.927
		60-69	.368	.155	.086
		70+	**.678***	**.158**	**.000**
	50-59	18-49	-.095	.154	.927
		60-69	.274	.163	.338
		70+	**.584***	**.166**	**.003**
	60-69	18-49	-.368	.155	.086
		50-59	-.274	.163	.338
		70+	.310	.167	.250
	70+	18-49	**-.678***	**.158**	**.000**
		50-59	**-.584***	**.166**	**.003**
		60-69	-.310	.167	.250

*. The mean difference is significant at the 0.05 level.

Multivariate MANOVA Analysis of RE and SE by AGE

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
20.907	1.339	15	12,418.026	**.169**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	125.457	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.965	3097.475[b]	2	223	.000	.965
	Wilks' Lambda	.035	3097.475[b]	2	223	.000	.965
	Hotelling's Trace	27.780	3097.475[b]	2	223	.000	.965
	Roy's Largest Root	27.780	3097.475[b]	2	223	.000	.965
AGE	Pillai's Trace	.163	3.965	10	448	**.000**	.081
	Wilks' Lambda	.843	3.981[b]	10	446	**.000**	.082
	Hotelling's Trace	.180	3.998	10	444	**.000**	.083
	Roy's Largest Root	.131	5.872[c]	5	224	**.000**	.116

a. Design: Intercept + AGE

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Gender

Construct	Gender	N	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Female	108	4.994	4.789	5.199	1.259	1.259	1.212	0.272
	Male	122	5.142	4.969	5.315				
	Total	230	5.072	4.940	5.205				
VUL	Female	108	5.370	5.157	5.583	0.000	0.000	0.000	0.992
	Male	122	5.369	5.178	5.560				
	Total	230	5.370	5.228	5.511				
ADOPT	Female	108	5.383	5.158	5.607	1.492	1.492	1.023	0.313
	Male	122	5.221	5.000	5.443				
	Total	230	5.297	5.140	5.454				
RE	Female	108	5.451	5.270	5.633	0.036	0.036	0.041	0.839
	Male	122	5.426	5.261	5.591				
	Total	230	5.438	5.317	5.559				
PTTF	Female	108	5.309	5.143	5.474	0.154	0.154	0.194	0.660
	Male	122	5.257	5.094	5.420				
	Total	230	5.281	5.166	5.397				
SE	Female	108	5.192	5.012	5.373	0.094	0.094	0.109	0.742
	Male	122	5.152	4.988	5.315				
	Total	230	5.171	5.050	5.291				
PAM	Female	108	70.306	67.062	73.551	12.239	12.239	0.048	0.826
	Male	122	69.844	67.181	72.507				
	Total	230	70.061	67.999	72.123				
RC	Female	108	4.257	4.050	4.464	2.826	2.826	2.002	0.158
	Male	122	4.035	3.807	4.263				
	Total	230	4.1391	3.984	4.293				

Multivariate MANOVA Analysis of RE and SE by GENDER

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
1.883	.622	3	17,841,468.948	**.601**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	136.073	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.975	4431.573[b]	2	227	.000	.975
	Wilks' Lambda	.025	4431.573[b]	2	227	.000	.975
	Hotelling's Trace	39.045	4431.573[b]	2	227	.000	.975
	Roy's Largest Root	39.045	4431.573[b]	2	227	.000	.975
GENDER	Pillai's Trace	.000	.055[b]	2	227	.947	.000
	Wilks' Lambda	1.000	.055[b]	2	227	.947	.000
	Hotelling's Trace	.000	.055[b]	2	227	.947	.000
	Roy's Largest Root	.000	.055[b]	2	227	.947	.000

a. Design: Intercept + GENDER

b. Exact statistic

Education

Construct	Education	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Some College/University or Less	94	4.927	4.704	5.151	3.564	3.564	3.471	0.064
	College/University Degree	133	5.182	5.018	5.345				
	Total	227	5.076	4.943	5.210				
VUL	Some College/University or Less	94	5.364	5.142	5.587	0.034	0.034	0.029	0.866
	College/University Degree	133	5.389	5.203	5.576				
	Total	227	5.379	5.237	5.521				
ADOPT	Some College/University or Less	94	5.195	4.964	5.426	1.704	1.704	1.162	0.282
	College/University Degree	133	5.371	5.154	5.588				
	Total	227	5.298	5.140	5.456				
RE	Some College/University or Less	94	5.420	5.233	5.607	0.107	0.107	0.122	0.727
	College/University Degree	133	5.464	5.301	5.628				
	Total	227	5.446	5.324	5.568				
PTTF	Some College/University or Less	94	5.234	5.055	5.413	0.415	0.415	0.521	0.471
	College/University Degree	133	5.321	5.166	5.476				
	Total	227	5.285	5.168	5.401				
SE	Some College/University or Less	94	5.096	4.923	5.269	1.156	1.156	1.365	0.244
	College/University Degree	133	5.241	5.074	5.407				
	Total	227	5.181	5.060	5.301				
PAM	Some College/University or Less	94	66.573	63.166	69.981	2,078	2,078	8.456	**0.004**
	College/University Degree	133	72.717	70.149	75.284				
	Total	227	70.173	68.089	72.257				
RC	Some College/University or Less	94	4.162	3.955	4.370	0.191	0.191	0.135	0.714
	College/University Degree	133	4.103	3.880	4.326				
	Total	227	4.128	3.972	4.283				

Multivariate MANOVA Analysis of RE and SE by EDUCATION

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
18.986	1.510	12	8713.458	**.112**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	129.006	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.949	2067.853[b]	2	221	.000	.949
	Wilks' Lambda	.051	2067.853[b]	2	221	.000	.949
	Hotelling's Trace	18.714	2067.853[b]	2	221	.000	.949
	Roy's Largest Root	18.714	2067.853[b]	2	221	.000	.949
EDUCATION	Pillai's Trace	.035	.976	8	444	.454	.017
	Wilks' Lambda	.966	.973[b]	8	442	.457	.017
	Hotelling's Trace	.035	.970	8	440	.459	.017
	Roy's Largest Root	.025	1.366[c]	4	222	.247	.024

a. Design: Intercept + EDUCATION

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Income

Construct	Income	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	< $50,000	91	5.090	4.862	5.318	3.448	1.724	1.657	0.193
	$50,000 - $74,999	60	4.958	4.703	5.214				
	$75,000 +	52	5.308	5.053	5.562				
	Total	203	5.107	4.965	5.248				
VUL	< $50,000	91	5.420	5.188	5.652	1.644	0.822	0.761	0.469
	$50,000 - $74,999	60	5.288	5.037	5.538				
	$75,000 +	52	5.529	5.255	5.802				
	Total	203	5.409	5.265	5.553				
ADOPT	< $50,000	91	5.205	4.943	5.468	8.197	4.098	2.897	0.058
	$50,000 - $74,999	60	5.178	4.862	5.493				
	$75,000 +	52	5.654	5.373	5.934				
	Total	203	5.312	5.146	5.478				
RE	< $50,000	91	5.407	5.201	5.612	2.357	1.178	1.395	0.250
	$50,000 - $74,999	60	5.358	5.138	5.579				
	$75,000 +	52	5.630	5.387	5.872				
	Total	203	5.450	5.322	5.577				
PTTF	< $50,000	91	5.278	5.083	5.474	1.060	0.530	0.657	0.519
	$50,000 - $74,999	60	5.211	4.980	5.442				
	$75,000 +	52	5.404	5.174	5.634				
	Total	203	5.291	5.167	5.415				
SE	< $50,000	91	5.165	4.963	5.367	3.791	1.895	2.324	0.101
	$50,000 - $74,999	60	5.079	4.869	5.290				
	$75,000 +	52	5.433	5.188	5.677				
	Total	203	5.208	5.082	5.334				
PAM	< $50,000	91	67.865	64.187	71.542	1,596.6	798.3	3.392	**0.036**
	$50,000 - $74,999	60	70.202	66.956	73.447				
	$75,000 +	52	74.808	70.968	78.647				
	Total	203	70.334	68.186	72.482				
RC	< $50,000	91	4.187	3.962	4.412	0.907	0.453	0.299	0.742
	$50,000 - $74,999	60	4.033	3.699	4.367				
	$75,000 +	52	4.164	3.775	4.552				
	Total	203	4.136	3.966	4.305				

Multiple Comparisons (Tukey's HSD)

Dependent Variable	(I) INCOME	(J) INCOME	Mean Difference (I-J)	Std. Error	Sig.
PAM	< $50,000	$50,000 - $74,999	-2.337	2.551	.631
		$75,000 +	**-6.943***	**2.667**	**.027**
	$50,000 - $74,999	< $50,000	2.337	2.551	.631
		$75,000 +	-4.606	2.907	.255
	$75,000 +	< $50,000	**6.943***	**2.667**	**.027**
		$50,000 - $74,999	4.606	2.907	.255

* The mean difference is significant at the 0.05 level.

Multivariate MANOVA Analysis of RE and SE by INCOME

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
13.256	.838	15	6,729.354	**.635**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	117.876	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.959	2284.061[b]	2	196	.000	.959
	Wilks' Lambda	.041	2284.061[b]	2	196	.000	.959
	Hotelling's Trace	23.307	2284.061[b]	2	196	.000	.959
	Roy's Largest Root	23.307	2284.061[b]	2	196	.000	.959
INCOME	Pillai's Trace	.057	1.158	10	394	.318	.029
	Wilks' Lambda	.943	1.164[b]	10	392	.314	.029
	Hotelling's Trace	.060	1.170	10	390	.310	.029
	Roy's Largest Root	.055	2.164[c]	5	197	.060	.052

a. Design: Intercept + INCOME

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Type 2 Diabetes Knowledge

Construct	Type 2 Diabetes Knowledge	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Poor to Fair	58	5.083	4.828	5.339	4.483	2.242	2.169	0.117
	Good	116	5.180	5.001	5.359				
	Very good to Excellent	55	4.833	4.524	5.142				
	Total	229	5.072	4.939	5.205				
VUL	Poor to Fair	58	5.224	4.930	5.519	4.176	2.088	1.768	0.173
	Good	116	5.502	5.323	5.682				
	Very good to Excellent	55	5.241	4.900	5.582				
	Total	229	5.369	5.227	5.511				
ADOPT	Poor to Fair	58	5.293	5.018	5.568	0.354	0.177	0.120	0.887
	Good	116	5.328	5.102	5.554				
	Very good to Excellent	55	5.230	4.867	5.594				
	Total	229	5.295	5.138	5.453				
RE	Poor to Fair	58	5.392	5.156	5.629	4.640	2.320	2.688	0.070
	Good	116	5.565	5.399	5.730				
	Very good to Excellent	55	5.218	4.944	5.493				
	Total	229	5.438	5.316	5.560				
PTTF	Poor to Fair	58	5.270	5.067	5.473	0.386	0.193	0.242	0.785
	Good	116	5.313	5.143	5.483				
	Very good to Excellent	55	5.212	4.958	5.466				
	Total	229	5.278	5.162	5.394				
SE	Poor to Fair	58	5.095	4.880	5.310	1.503	0.751	0.872	0.420
	Good	116	5.248	5.067	5.429				
	Very good to Excellent	55	5.077	4.830	5.325				
	Total	229	5.168	5.047	5.289				
PAM	Poor to Fair	58	63.234	59.153	67.316	5,668	2,834	12.359	**0.000**
	Good	116	70.111	67.292	72.930				
	Very good to Excellent	55	77.404	73.534	81.273				
	Total	229	70.121	68.053	72.189				
RC	Poor to Fair	58	4.323	4.077	4.570	4.133	2.067	1.469	0.232
	Good	116	4.127	3.879	4.375				
	Very good to Excellent	55	3.941	3.659	4.223				
	Total	229	4.132	3.977	4.287				

Multiple Comparisons (Tukey's HSD)

Dependent Variable	(I) Type 2 Diabetes Knowledge	(J) Type 2 Diabetes Knowledge	Mean Difference (I-J)	Std. Error	Sig.
PAM	Poor to Fair	Good	**-6.877***	**2.435**	**.014**
		Very good to Excellent	**-14.169***	**2.850**	**.000**
	Good	Poor to Fair	**6.877***	**2.435**	**.014**
		Very good to Excellent	**-7.292***	**2.479**	**.010**
	Very good to Excellent	Poor to Fair	**14.169***	**2.850**	**.000**
		Good	**7.292***	**2.479**	**.010**

* The mean difference is significant at the 0.05 level.

Multivariate MANOVA Analysis of RE and SE by Type 2 Diabetes Knowledge (T2KNOWLEDGE)

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
11.745	.812	12	441.445	**.638**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	132.472	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.878	801.006[b]	2	223	.000	.878
	Wilks' Lambda	.122	801.006[b]	2	223	.000	.878
	Hotelling's Trace	7.184	801.006[b]	2	223	.000	.878
	Roy's Largest Root	7.184	801.006[b]	2	223	.000	.878
T2KNOWLEDGE	Pillai's Trace	.040	1.131	8	448	.341	.020
	Wilks' Lambda	.961	1.129[b]	8	446	.342	.020
	Hotelling's Trace	.041	1.126	8	444	.344	.020
	Roy's Largest Root	.030	1.691[c]	4	224	.153	.029

a. Design: Intercept + T2KNOWLEDGE

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Type 2 Diabetes Control

Construct	Type 2 Diabetes Control	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Very Poor to Moderate	132	5.331	5.180	5.481	20.865	20.865	21.812	**0.000**
	Well to Very Well	97	4.720	4.497	4.943				
	Total	229	5.072	4.939	5.205				
VUL	Very Poor to Moderate	132	5.591	5.418	5.763	15.346	15.346	13.623	**0.000**
	Well to Very Well	97	5.067	4.838	5.296				
	Total	229	5.369	5.227	5.511				
ADOPT	Very Poor to Moderate	132	5.386	5.191	5.582	2.574	2.574	1.762	0.186
	Well to Very Well	97	5.172	4.909	5.434				
	Total	229	5.295	5.138	5.453				
RE	Very Poor to Moderate	132	5.492	5.340	5.645	0.931	0.931	1.063	0.304
	Well to Very Well	97	5.363	5.162	5.565				
	Total	229	5.438	5.316	5.560				
PTTF	Very Poor to Moderate	132	5.303	5.151	5.456	0.195	0.195	0.245	0.621
	Well to Very Well	97	5.244	5.063	5.425				
	Total	229	5.278	5.162	5.394				
SE	Very Poor to Moderate	132	5.174	5.013	5.335	0.012	0.012	0.014	0.908
	Well to Very Well	97	5.160	4.974	5.346				
	Total	229	5.168	5.047	5.289				
PAM	Very Poor to Moderate	132	66.856	64.178	69.534	3,322	3,322	13.921	**0.000**
	Well to Very Well	97	74.564	71.481	77.647				
	Total	229	70.121	68.053	72.189				
RC	Very Poor to Moderate	132	4.205	3.998	4.411	1.636	1.636	1.159	0.283
	Well to Very Well	97	4.034	3.797	4.270				
	Total	229	4.132	3.977	4.287				

Multivariate MANOVA Analysis of RE and SE by Type 2 Diabetes Control (T2CONTROL)

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
5.263	.564	9	17,876.024	**.827**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	129.431	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.803	455.717[b]	2	223	.000	.803
	Wilks' Lambda	.197	455.717[b]	2	223	.000	.803
	Hotelling's Trace	4.087	455.717[b]	2	223	.000	.803
	Roy's Largest Root	4.087	455.717[b]	2	223	.000	.803
T2CONTROL	Pillai's Trace	.051	1.467	8	448	.167	.026
	Wilks' Lambda	.949	1.474[b]	8	446	.164	.026
	Hotelling's Trace	.053	1.481	8	444	.162	.026
	Roy's Largest Root	.049	2.760[c]	4	224	.029	.047

a. Design: Intercept + T2CONTROL

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Type 2 Diabetes Duration

Construct	Time Since Type 2 Diabetes Diagnosis	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	< 10 years	134	5.051	4.892	5.210	0.175	0.175	0.170	0.680
	10 + years	93	5.108	4.876	5.339				
	Total	227	5.074	4.942	5.207				
VUL	< 10 years	134	5.328	5.153	5.504	0.695	0.695	0.593	0.442
	10 + years	93	5.441	5.202	5.679				
	Total	227	5.374	5.233	5.516				
ADOPT	< 10 years	134	5.348	5.160	5.536	0.823	0.823	0.562	0.454
	10 + years	93	5.226	4.947	5.505				
	Total	227	5.298	5.140	5.456				
RE	< 10 years	134	5.513	5.372	5.654	1.827	1.827	2.104	0.148
	10 + years	93	5.331	5.111	5.550				
	Total	227	5.438	5.316	5.561				
PTTF	< 10 years	134	5.281	5.144	5.419	0.001	0.001	0.002	0.966
	10 + years	93	5.276	5.072	5.480				
	Total	227	5.279	5.164	5.394				
SE	< 10 years	134	5.218	5.075	5.361	0.884	0.884	1.032	0.311
	10 + years	93	5.091	4.877	5.306				
	Total	227	5.166	5.045	5.287				
PAM	< 10 years	134	69.340	66.692	71.987	183.92	183.92	0.740	0.390
	10 + years	93	71.170	67.846	74.494				
	Total	227	70.089	68.029	72.150				
RC	< 10 years	134	4.218	4.018	4.419	3.017	3.017	2.166	0.143
	10 + years	93	3.984	3.738	4.229				
	Total	227	4.122	3.968	4.277				

Multivariate MANOVA Analysis of RE and SE by Duration since Type 2 Diabetes Diagnosis (T2DURATION)

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
24.658	1.909	12	1,978.209	.029

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	128.466	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.893	914.256[b]	2	220	.000	.893
	Wilks' Lambda	.107	914.256[b]	2	220	.000	.893
	Hotelling's Trace	8.311	914.256[b]	2	220	.000	.893
	Roy's Largest Root	8.311	914.256[b]	2	220	.000	.893
T2DURATION	Pillai's Trace	.055	1.250	10	442	.257	.027
	Wilks' Lambda	.946	1.245[b]	10	440	.260	.028
	Hotelling's Trace	.057	1.240	10	438	.263	.028
	Roy's Largest Root	.034	1.504[c]	5	221	.190	.033

a. Design: Intercept + T2DURATION

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

General Health Condition

Construct	General Health Condition	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Poor or Fair	71	5.211	4.950	5.473	1.572	1.572	1.520	0.219
	Good, Very Good or Excellent	154	5.031	4.876	5.186				
	Total	225	5.088	4.954	5.222				
VUL	Poor or Fair	71	5.500	5.243	5.757	1.466	1.466	1.226	0.269
	Good, Very Good or Excellent	154	5.326	5.152	5.501				
	Total	225	5.381	5.237	5.525				
ADOPT	Poor or Fair	71	5.272	5.025	5.519	0.123	0.123	0.083	0.773
	Good, Very Good or Excellent	154	5.323	5.119	5.526				
	Total	225	5.307	5.148	5.466				
RE	Poor or Fair	71	5.377	5.188	5.565	0.523	0.523	0.598	0.440
	Good, Very Good or Excellent	154	5.481	5.323	5.639				
	Total	225	5.448	5.325	5.571				
PTTF	Poor or Fair	71	5.230	5.026	5.434	0.274	0.274	0.344	0.558
	Good, Very Good or Excellent	154	5.305	5.161	5.450				
	Total	225	5.281	5.164	5.399				
SE	Poor or Fair	71	5.109	4.900	5.318	0.473	0.473	0.554	0.457
	Good, Very Good or Excellent	154	5.208	5.058	5.358				
	Total	225	5.177	5.056	5.298				
PAM	Poor or Fair	71	62.782	59.075	66.489	5,761	5,761	25.655	**0.000**
	Good, Very Good or Excellent	154	73.669	71.335	76.004				
	Total	225	70.234	68.160	72.308				
RC	Poor or Fair	71	4.493	4.281	4.705	13.005	13.005	9.443	**0.002**
	Good, Very Good or Excellent	154	3.976	3.772	4.180				
	Total	225	4.139	3.982	4.296				

Multivariate MANOVA Analysis of RE and SE by General Health Condition (GENERALHEALTH)

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
27.677	1.976	12	471.608	.025

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	126.389	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.907	1071.889[b]	2	219	.000	.907
	Wilks' Lambda	.093	1071.889[b]	2	219	.000	.907
	Hotelling's Trace	9.789	1071.889[b]	2	219	.000	.907
	Roy's Largest Root	9.789	1071.889[b]	2	219	.000	.907
GENERAL HEALTH	Pillai's Trace	.025	.709	8	440	.684	.013
	Wilks' Lambda	.975	.708[b]	8	438	.685	.013
	Hotelling's Trace	.026	.707	8	436	.685	.013
	Roy's Largest Root	.022	1.212[c]	4	220	.307	.022

a. Design: Intercept + GENERALHEALTH

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

General Health Knowledge

Construct	General Health Knowledge	n	Mean	95% Confidence Interval for Mean		ANOVA			
				Lower Bound	Upper Bound	Sum of Squares	Mean Square	F	Sig.
SEV	Poor, Fair or Good	158	5.259	5.115	5.404	18.535	18.535	19.076	**0.000**
	Very Good or Excellent	67	4.632	4.358	4.906				
	Total	225	5.073	4.938	5.207				
VUL	Poor, Fair or Good	158	5.514	5.361	5.668	10.870	10.870	9.440	**0.002**
	Very Good or Excellent	67	5.034	4.723	5.345				
	Total	225	5.371	5.228	5.515				
ADOPT	Poor, Fair or Good	158	5.295	5.112	5.479	0.000	0.000	0.000	0.992
	Very Good or Excellent	67	5.294	4.971	5.616				
	Total	225	5.295	5.136	5.454				
RE	Poor, Fair or Good	158	5.473	5.335	5.611	0.543	0.543	0.620	0.432
	Very Good or Excellent	67	5.366	5.108	5.623				
	Total	225	5.441	5.318	5.564				
PTTF	Poor, Fair or Good	158	5.272	5.134	5.410	0.002	0.002	0.002	0.961
	Very Good or Excellent	67	5.279	5.048	5.509				
	Total	225	5.274	5.156	5.392				
SE	Poor, Fair or Good	158	5.176	5.036	5.316	0.043	0.043	0.049	0.825
	Very Good or Excellent	67	5.146	4.895	5.397				
	Total	225	5.167	5.044	5.289				
PAM	Poor, Fair or Good	158	66.316	63.940	68.692	7,559	7,559	34.103	**0.000**
	Very Good or Excellent	67	78.991	75.499	82.483				
	Total	225	70.090	67.995	72.186				
RC	Poor, Fair or Good	158	4.242	4.060	4.425	5.651	5.651	4.022	**0.046**
	Very Good or Excellent	67	3.896	3.593	4.198				
	Total	225	4.139	3.982	4.296				

Multivariate MANOVA Analysis of RE and SE by General Health Knowledge (HEALTHKNOWLEDGE)

Box's Test of Equality of Covariance Matrices

Box's M	F	df1	df2	Sig.
12.874	1.368	9	5,629.319	**.197**

Bartlett's Test of Sphericity

Likelihood Ratio	Approx. Chi-Square	df	Sig.
.000	131.473	2	**.000**

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.871	739.454[b]	2	219	.000	.871
	Wilks' Lambda	.129	739.454[b]	2	219	.000	.871
	Hotelling's Trace	6.753	739.454[b]	2	219	.000	.871
	Roy's Largest Root	6.753	739.454[b]	2	219	.000	.871
HEALTH KNOWLEDGE	Pillai's Trace	.035	.979	8	440	.452	.017
	Wilks' Lambda	.965	.976[b]	8	438	.454	.018
	Hotelling's Trace	.036	.973	8	436	.456	.018
	Roy's Largest Root	.026	1.414[c]	4	220	.230	.025

a. Design: Intercept + HEALTHKNOWLEDGE

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

Appendix Q – PLS Model Control Variable Analysis

Demographic Control Variables

Demographic Control Variable Path Analysis

	Age →		Gender →		Education →		Income →	
	Path	Sig.	Path	Sig.	Path	Sig.	Path	Sig.
ADOPT	-0.059	1.726 ns	-0.044	1.373 ns	0.065	1.668 ns	0.085	2.800 **
PTTF	-0.136	2.562 *	-0.048	1.107 ns	-0.007	0.186 ns	0.013	0.288 ns
RE	-0.167	3.075 **	-0.032	0.807 ns	0.045	0.975 ns	0.082	1.480 ns
SE	-0.151	2.650 **	-0.035	0.820 ns	0.041	0.861 ns	0.088	1.524 ns

*Note: ns=not significant, *=p<.05, **=p<.01*

Demographic Control Variable R^2 and Effect Size Analysis

	Age				Gender				Education				Income			
	R^2In	R^2Out	f^2	ES	R^2In	R^2Out	f^2	ES	R^2In	R^2Out	f^2	ES	R^2In	R^2Out	f^2	ES
ADOPT	0.679	0.675	0.012	ns	0.677	0.675	0.006	ns	0.679	0.675	0.012	ns	0.682	0.675	0.022	SM
PTTF	0.269	0.252	0.023	SM	0.254	0.252	0.003	ns	0.252	0.252	0.000	ns	0.252	0.252	0.000	ns
RE	0.246	0.220	0.034	SM	0.221	0.220	0.001	ns	0.222	0.220	0.003	ns	0.226	0.22	0.008	ns
SE	0.234	0.214	0.026	SM	0.215	0.214	0.001	ns	0.215	0.214	0.001	ns	0.221	0.214	0.009	ns

Note: ns=not significant, SM=Small

Type 2 Diabetes Related Control Variables

Type 2 Diabetes Control Variable Path Analysis

	Type 2 Diabetes Knowledge →		Type 2 Diabetes Control →		Type 2 Diabetes Duration →	
	Path	Sig.	Path	Sig.	Path	Sig.
ADOPT	0.009	0.348 ns	-0.036	1.147 ns	0.018	0.726 ns
PTTF	-0.086	1.525 ns	0.112	1.979 ns	-0.038	1.001 ns
RE	-0.063	1.325 ns	0.082	1.534 ns	-0.122	2.104 *
SE	-0.115	1.967 ns	0.040	0.863 ns	-0.123	2.249 *

*Note: ns=not significant, *=p<.05*

Type 2 Diabetes Control Variable R^2 and Effect Size Analysis

	Type 2 Diabetes Knowledge				Type 2 Diabetes Control				Type 2 Diabetes Duration			
	R^2In	R^2Out	f^2	ES	R^2In	R^2Out	f^2	ES	R^2In	R^2Out	f^2	ES
ADOPT	0.675	0.675	0.000	ns	0.677	0.675	0.006	ns	0.676	0.675	0.003	ns
PTTF	0.258	0.252	0.008	ns	0.262	0.252	0.014	ns	0.253	0.252	0.001	ns
RE	0.224	0.220	0.005	ns	0.226	0.22	0.008	ns	0.234	0.22	0.018	ns
SE	0.225	0.214	0.014	ns	0.215	0.214	0.001	ns	0.229	0.214	0.019	ns

Note: ns=not significant, SM=Small

General Health Related Control Variables

General Health Control Variable Path Analysis

	General Health Condition →		General Health Knowledge →	
	Path	**Sig.**	**Path**	**Sig.**
ADOPT	0.002	0.080 ns	-0.004	0.160 ns
PTTF	0.050	1.068 ns	-0.012	0.317 ns
RE	0.121	2.300 *	0.041	0.979 ns
SE	0.083	1.478 ns	-0.019	0.436 ns

*Note: ns=not significant, *=p<.05*

General Health Control Variable R^2 and Effect Size Analysis

	General Health Condition				General Health Knowledge			
	R^2In	**R^2Out**	**f^2**	**ES**	**R^2In**	**R^2Out**	**f^2**	**ES**
ADOPT	0.675	0.675	0.000	ns	0.675	0.675	0.000	ns
PTTF	0.254	0.252	0.003	ns	0.252	0.252	0.000	ns
RE	0.234	0.220	0.018	ns	0.221	0.220	0.001	ns
SE	0.220	0.214	0.008	ns	0.214	0.214	0.000	ns

Note: ns=not significant