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ABSTRACT

Health is a fully individualized concern, and is therefore inherently mobile. Thus, Ubiquitous Healthcare Information Systems can enable a much-needed patient-centered care environment. This paper presents a decision support system that makes use of system dynamics methodologies in order to assess the improved health benefits that may be realized within the context of ubiquitous healthcare information systems in support of managing diabetes.

Keywords

Ubiquitous Healthcare Information System, pervasive technology, System Dynamics, DSS, patient-centered care, health benefits

INTRODUCTION

Ubiquitous Healthcare Information Systems (UHIS), in which pervasive and ubiquitous consumer technologies interoperate with healthcare providers' information systems to monitor and exchange patient medical information, have three primary objectives: to reduce time loss due to lag, to reduce inaccuracies in traditional medical information flows, and to reduce the costs of information flow (Joo-hak, 2008). Lag refers to the time required for acquiring information from paper-based systems or personal contact, for example, in order to inform treatment plan decisions. A reduction in lag can reduce the gap between when data is recorded and when that information is available for processing in support of treatment plan decisions. To assess the benefits over time of UHIS in support of managing a chronic medical condition such as diabetes, we present a decision support system that makes use of system dynamics modeling techniques.

UHIS are advocated to support patients' compliance with commonly accepted care plans, and to help detect patients' medical conditions in real time, thereby improving diagnoses (Dishman, 2004). They take on a range of forms, from pervasive and ubiquitous technologies such Internet access, mobile phones and PDAs, to specialized technologies that are worn by or embedded in patients and become an unobtrusive part of patients' daily lives (*ibid.*; Korhonen and Bardram, 2004). Examples of current and future UHIS abound. Scholars contend, for example, that patients can benefit from participating in online health communities (*e.g.*, Johnson and Ambrose, 2006). Through social interaction with others that have experienced similar medical conditions, patients may receive affective and social support, and opportunities to discuss and enhance their comprehension of healthcare providers' advice and diagnoses. Consequently, online health communities may lead to improved compliance with commonly accepted care plans. Internet applications such as Microsoft HealthVault and Google Health also enable patients to record information about their medical indications (*e.g.*, weight and blood pressure) over time and aggregate data from healthcare providers in order to provide up-to-date information to doctors, specialists, emergency and other healthcare personnel (Steinbrook, 2008), in support of diagnosis and treatment. PDAs (personal digital assistants) and mobile phones offer a mobile platform for logging biological information (*e.g.*, blood glucose, pressure) and subsequently providing real-time guidance to the patient in support of compliance (*e.g.*, alerting the patient that

he/she needs more exercise) and/or submitting the information wirelessly to healthcare providers in support of diagnoses and adjustments to care plans (Korhonen and Bardram, 2004). Pundits also tout specialized technologies in the near future that are worn by or embedded in patients and that automatically monitor and log biological information to mobile phones or PDAs (Bonato, 2003) in support of diagnosis and care decisions. Specialized technologies ready for commercialization include wearable clothing, rings and sensors embedded in the bloodstream that can automatically monitor activity levels, blood pressure, and signs of seizures and cardiovascular events, for example, that signal and inform medical intervention to preempt serious medical complications. Researchers are also developing data mining techniques to analyze the copious amounts of data made available by UHIS, in order to identify meaningful information in support of actors' care plan decisions and diagnoses.

To highlight the significance of information flow among actors in support of diabetes management, Montazemi *et al.* (2009) applied a dependency network diagram (DND) analysis within the context of diabetes management in Canada. They find that although patients are well supported by personal communications with healthcare providers, at present patients are disenfranchised from information flows in healthcare providers' information systems and the potential of that information to support patients' participation in care decisions and self-care. Although DND provides a good representation of information dependencies among the actors, it doesn't allow decision makers (*i.e.*, policymakers) to assess the effects of a future UHIS. Therefore, the aim of this research is to present a decision support system (DSS) model to assess the possible benefits of using UHIS to diagnose medical conditions early and to support compliance with commonly accepted care plans.

The benefits of UHIS can be measured in the form of resulting improved operational efficiency and improved effectiveness in decision processes. Our focus in this paper is on the possible improved effectiveness of decision processes that would result in improved patient health status. Thus, the research question in this paper is 'How could we assess the possible effectiveness of ubiquitous healthcare information systems on patients' health status over time?' Our basic assumption is that UHIS would improve decision processes that result in improved diagnosis and improved control rates of patients' conditions and risk factors, in compliance with commonly accepted care plans. To this end, we propose a DSS that makes use of systems dynamics methodologies to simulate the possible improved effectiveness of UHIS on diabetes-related health status.

BACKGROUND

The context of managing diabetes in Canadian healthcare systems provides a poignant example of patient-centered care that relies on information exchange among patients and numerous healthcare providers in care management decisions. Scholars find that patients' active participation in diabetes management decisions can substantially mitigate the escalation of medical complications and associated treatment costs (Homer *et al.*, 2004a; Testa and Simonson, 1998; Wagner *et al.*, 2001) – costs that amounted to CAD$6 billion of the $54 billion Canada's provinces and territories spent on public healthcare in 2000 (PTMH, 2000). To that end, more than a decade of medical literature has advocated the redesign of chronic care management, such as diabetes, to a "patient-centered care" model (*e.g.*, Von Korff *et al.*, 1997; Wagner *et al.*, 1996) characterized by the exchange of all information relevant to decision-making between patients and healthcare providers (Bugge *et al.*, 2006). The redesign involves moving beyond a care model designed around providers managing illnesses, to a model designed around patients and providers proactively managing patients' self-care (Dishman, 2004; Korhonen and Bardram, 2004). In the redesign, information and communication technologies can play a major role by helping to "detect disease early and support compliance with commonly accepted care plans" (Dishman, 2004, p. 35). In particular, pervasive consumer technologies interoperating with healthcare providers' information systems (i.e., UHIS) can enable real-time information exchange in support of prevention, diagnosis, and treatment. Prevention, diagnosis and treatment are important factors in the escalation of diabetes over time.

Diabetes mellitus is a chronic condition that tends to escalate throughout patients' life cycles (see Figure 1), especially if left undetected and uncontrolled (D'Cruz, 2008). The normoglycemic population refers to individuals whose blood glucose levels remain within a commonly accepted range. The pre-diabetic stage refers to individuals who have amplified risk factors for diabetes, such as obesity and aging, and whose blood glucose levels hover around the upper level of the commonly accepted normoglycemic range. In the third stage, the individual is diagnosed with diabetes. Their blood glucose levels frequently exceed the normoglycemic range, which amplifies their risk of experiencing fourth-stage medical complications such as stroke, heart attack, vision problems and foot disorders (O'Reilly *et al.*, 2007). Therefore, patients' health status deteriorates with the escalation of diabetes, and the overarching objective of diabetes health care is to mitigate escalation. Escalation can be substantially mitigated provided that risk factors and medical conditions are accurately diagnosed (*i.e.*, detected), and the patient complies

with medical best practices in prevention, monitoring and control of their risk factors (*e.g.*, through diet and exercise) and medical conditions (*e.g.*, monitoring blood glucose, administering insulin) (ADA, 2003; Testa and Simonson, 1998; Wagner *et al.*, 2001). Management of diabetes is necessarily patient-centered because substantial segments of the management – diet, exercise, self-monitoring and medication use, for example – rely on the actions of patients over their life cycles (Bodenheimer *et al.*, 2002; Wagner *et al.,* 1996). However, numerous healthcare providers with specialized knowledge play a role in informing treatment plan decisions.

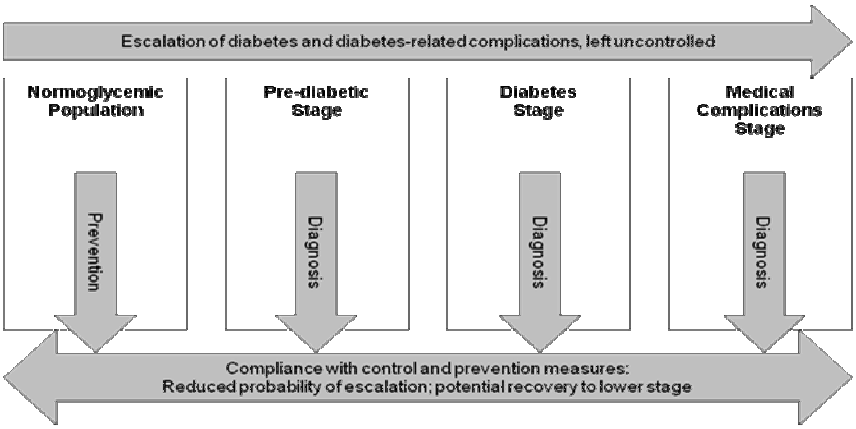

Figure 1. Conceptual illustration of the escalation of diabetes through patients' life cycles

THEORETICAL FOUNDATION

Actors involved in patient-centered care (*i.e.*, patients, physicians, nurses, dieticians, medical laboratory technicians, pharmacists) apply their knowledge to acquire and share information relevant to coordinated treatment plans for a specific patient. Within this context, actors communicate with each other to reduce uncertainty, thereby making their decision environments more predictable (Te'eni, 2001). Communication among networked actors supplements information exchange by providing opportunities for clarification and sense-making regarding the potential impacts of alternative treatment strategies for a specific patient (Grabowski and Roberts, 1999). DND methodology affords a means to identify dependencies among the actors to get a sense of information flow among the actors. In accordance with the DND methodology (Tillquist *et al.*, 2002), Montazemi *et al.* (2009) identified distinct *goals* of actors that are expected to cumulate in the achievement of the overarching objective (*i.e.*, to manage patients' diabetic risks and conditions in order to mitigate escalation of medical complications over time). To accomplish each goal, actors must complete specific *actions*. They found that patients cannot complete the necessary actions without relying on information from multiple healthcare providers. Specifically, patients have information *dependencies* on multiple healthcare providers. In turn, healthcare providers take on care delivery goals and undertake actions that contribute to treatment plan decisions and implementation, which generates further information dependencies between healthcare providers in support of care delivery. *Coordination* refers to how actors interact and exchange information (*i.e.*, communicate) to satisfy their dependencies, and thereby form ties between actors. DND arranges these constructs – goals, actions, dependencies and coordination – diagrammatically to depict the structure of a network. Figure 2 illustrates the resulting DND for actors within the context of diabetes management in a Canadian healthcare system. The DND representation enables technological and organizational designers to assess organizational interfaces between interdependent actors, thereby uncovering opportunities to support actors' goal achievement by realigning their information dependencies.

Whereas the DND illustrates that information flows involving patients are not supported by integrated healthcare information systems, for example, the literature suggests several roles for UHIS. For example, patients with chronic conditions, such as diabetes, could use pervasive technologies to monitor their blood glucose level, compiling an accurate and timely record of their condition, and alerting their primary care physician when conditions are out of control (Korhonen and Bardram, 2004). Through interoperability with healthcare providers' information systems, pervasive technologies could enable remote monitoring of patients' conditions and compliance with treatment plans, and alert healthcare providers to intervene and advise as necessary. Nonetheless, investment in a future patient-centered information system requires significant investment. Therefore, policymakers need to know the significance of changes in health outcomes that arise from the application of UHIS in healthcare. For example, in regard to

Figure 2, decision makers need to know how significantly improvements in the diagnosis and control of patients' diabetes risks and conditions, made possible by UHIS, would improve patients' health status over time. To that end, we use systems dynamics methodologies in the form of a decision support system (DSS) in support of investment decisions by the policymakers.

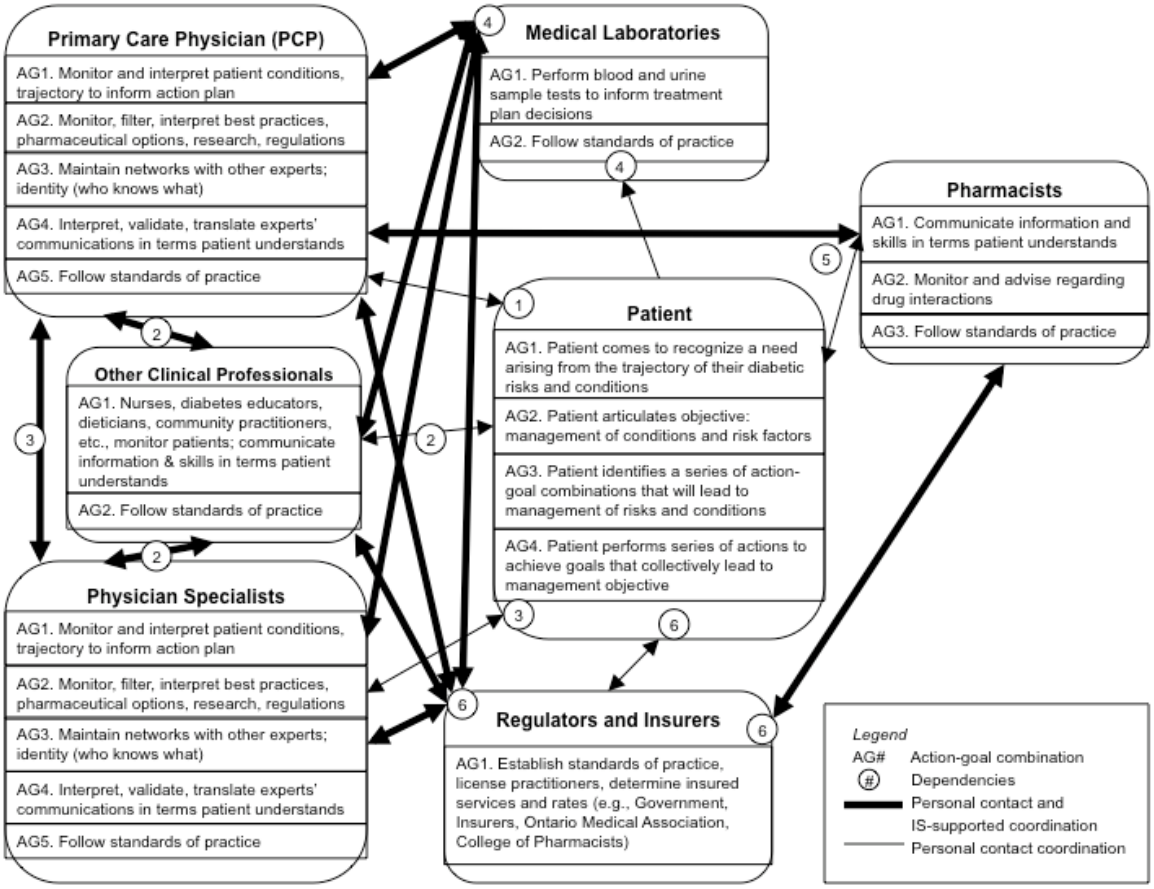

Figure 2. Dependency Network Diagram within the context of diabetes management (adopted from Montazemi *et al.*, 2009)

Whereas policymakers make investment decisions that affect the management of diabetes in a healthcare system, both the policymakers and the actors that comprise the system are subject to bounded rationality (*e.g.*, Forrester, 1961; Simon, 1957). The principle of bounded rationality recognizes that actors rely on simple decision-making routines that are subject to serious limitations. Simple routines become increasingly deficient for deciding optimal solutions as the numbers of interacting variables in a problem increase, as the pace of change in the environment increases, and as more people participate in key decisions. These characteristics constitute dynamic tensions that impact on the performance of actors and the systems they comprise. System dynamics (SD) is primarily a diagnostic and impact assessment method directed at finding out the effects of policy changes on the performance of systems characterized by dynamic tensions (Smits forthcoming; Sterman, 2000). In particular, SD is a suitable method to assess the possible impact of a UHIS environment on health outcomes in diabetes management because diabetes management meets the four conditions formulated by Smits (Forthcoming). First, because patients' health status at any time is a function of numerous conditions and interactions with healthcare providers, the problem is dynamic, it involves a large number of interacting variables, and outcomes cannot be easily foreseen without the help of a computer model. Second, the problem is 'long term' meaning that effects of a UHIS do not appear immediately but only after some period of time. Third, the problem statement includes a 'reference mode of behavior', meaning a comparison between a new situation (*i.e.*, a patient-centered design) and a current state of behavior. Fourth, the problem description gives rise to thinking in terms of flow processes, such as flows of patients through different stages of treatment processes.

MODEL DEVELOPMENT

Model Structure Overview

In this section, we describe the structure of the diabetes model from a system dynamics perspective. Appendix B presents the set of variables that comprise the model, and Figure 3 depicts the flow diagram of the model. In this model, the complex progression of diabetes has been modeled in four separate stages, *normoglycemic, pre-diabetes, diabetes, and diabetes with related medical complications*. In addition, this model presents the various dynamics involved in accelerating or decelerating the intensity of diabetes progression in the population. Population stocks are presented in rectangles and double thick arrows with valve symbols indicate flows. Other variables such as controlled fraction coefficients directly or indirectly affect the population flows among the stocks. We elaborate on the model as follows.

Population Stocks, Inflows, and Mortalities

The Canadian population has been divided into seven separate stocks, depicted in Figure 3, that represent distinct diabetes statuses within the population: (1) normoglycemic population (*i.e.* neither having nor particularly at risk for diabetes), (2) unidentified and (3) diagnosed pre-diabetics (*i.e.* at risk with a tendency to experience above-normal blood glucose), (4) unidentified and (5) diagnosed diabetics without medical complications (*i.e.* regularly experiencing blood glucose levels above normoglycemic levels), and (6) unidentified and (7) diagnosed diabetics with medical complications (*i.e.* having diabetes as well as diabetes-related medical complications such as stroke, heart attack, vision problems and foot disorders) (Agency for Healthcare Research and Quality, 2008; O'Reilly *et al.*, 2007). The sum of stocks in the model represents the entire population.

Stocks are interrelated through flow variables (Sterman, 2000). The population in each of the stocks is determined through trade-off between its inflows (*e.g.*, from other stocks) and outflows (*e.g.*, flows to other stocks and mortality). Like all flows in the model, population net inflow is expressed as persons per year. The net changes in the population and all mortality outflows are modeled to represent net of population inflows to the model based on a time series for the Canadian population (*cf.* http://datafinder.worldbank.org) and published projections of the Canadian population until 2050 (Bélanger *et al.*, 2005).

Mortality rates used for outflows from stocks in the model are functions of (i) a base population mortality rate, (ii) a coefficient representing the effect of diabetes stage for each respective stock, and (iii) a coefficient representing the population aging effect for each respective stock. The base population mortality rate in Canada is estimated at 0.763% per year (Bélanger *et al.*, 2005). The non-diabetic (*i.e.*, normoglycemic and pre-diabetes stages) population experiences lower mortality rates than the overall population by a coefficient of 1.0/1.2, due to younger-than-average age of the non-diabetic population (Homer *et al.,* 2004b). We also computed a population aging effect based on a time series of the elderly (*i.e.*, age 65-plus) proportion of the Canadian population (Bélanger *et al.*, 2005; Statistics Canada, 2007), in which the mortality rate is higher by a coefficient of 8.0 than the population average (Homer *et al.*, 2004b). Therefore, the product of base rate, stage and aging effect were applied to the mortality rate (outflow) from stocks with normoglycemic and pre-diabetic stages. To account for higher mortality rates for stocks in the diabetes stage, a coefficient of 1.4/1.2 was applied (*ibid.*). Another coefficient of 1.9x8.0 was applied to account for the disproportionately higher number of elderly in this stage (*ibid.*). The base mortality rate for the undiagnosed stock in the diabetes stage rises to 12% per year (*ibid.*). This rate is further adjusted for the diagnosed stock in the medical complications stage based on the prorated proportion of patients who have their condition controlled (relative mortality risk of 16.7%) or uncontrolled (relative mortality risk of 46.5%) (*ibid.*). Finally, the mortality rate for both stocks in the medical complications stage is also age-adjusted at a coefficient of 7.6x8.0 (*ibid.*). Next, we will explain the interrelating flow rates between the stock variables.

Onset, Progression, and Recovery rates

Pre-diabetes Onset and Recovery Rates. We assume that pre-diabetes is the precursor to diabetes. Obesity and elderly are two factors that substantially change the risk of escalating from normoglycemic to pre-diabetes (Canada Safety Council, 2006; Canadian Diabetes Association, 2008a, 2008b; Homer *et al.*, 2004b; Homer *et al.*, 2004c; Homer and Hirsch, 2006; Honeycutt *et al.*, 2003; Luo *et al.*, 2007; Wagner *et al.*, 2001). Based on the available data for prevalence of pre-diabetes (Homer *et al.*, 2004b), we estimate the average annual onset rate of pre-diabetes for the non-elderly and non-obese population as 4.3% per year, and coefficients of 2.6 for obese and 1.15 for elderly proportions of the population (*ibid.*) based on time series for obesity (Le-Petit, 2005; Luo *et al.*, 2007; Tjepkema, 2004, 2006) and elderly (Bélanger *et al.*, 2005; George *et al.*, 2001; Statistics Canada, 2007) population composition. Recovery from pre-diabetes stage is affected by the changes in patients' diets and lifestyles that bring

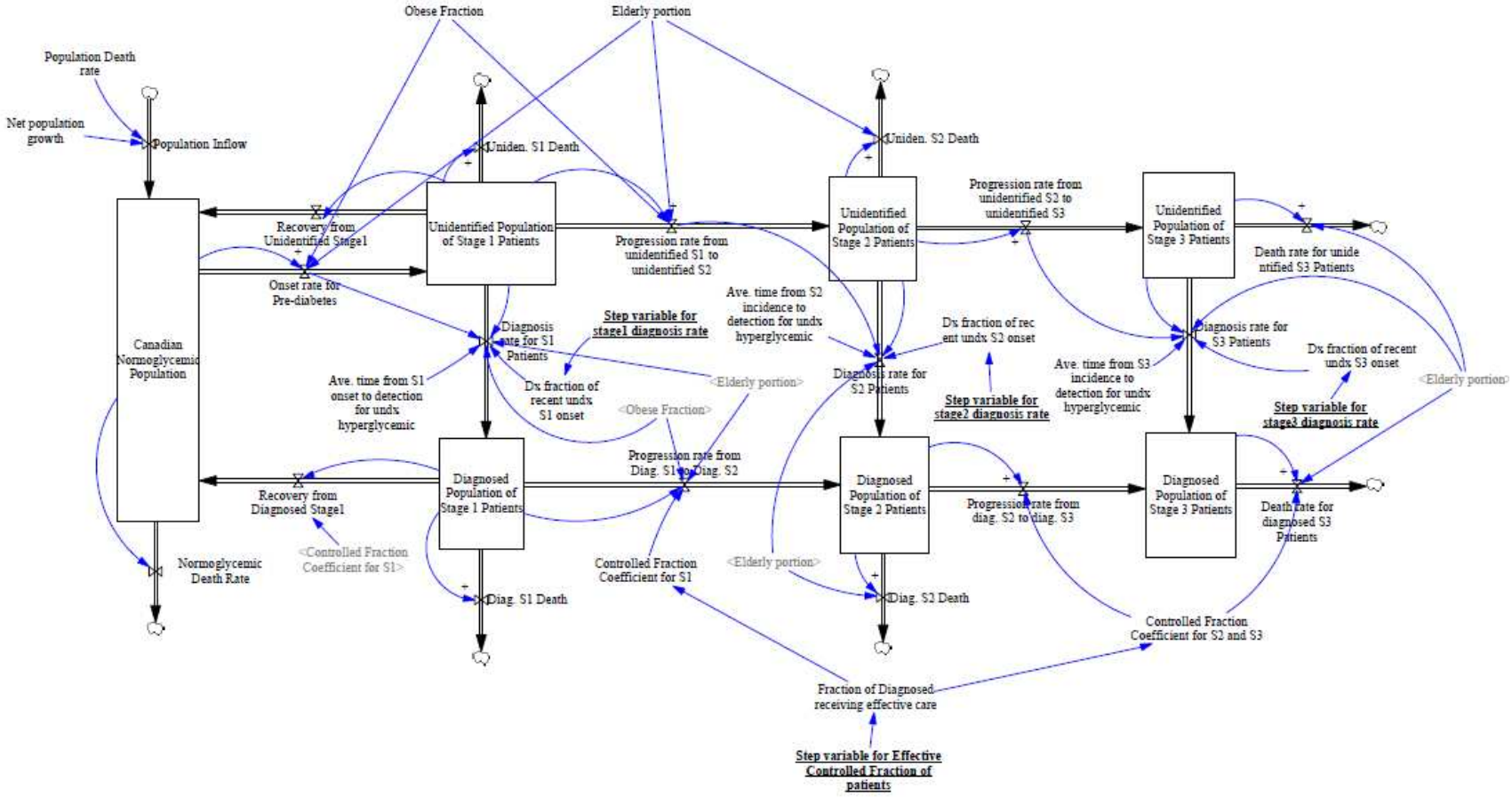

Figure 3. Dynamic model of diabetes

diabetes conditions and risk factors under control (O'Reilly *et al.*, 2007). We estimate the normal rate of recovery from pre-diabetes as 10%, with a coefficient of 1.5 for the prorated portion of diagnosed pre-diabetics that have their condition and risks under control, and 50% of any reductions in the incidence of obesity is added to the recovery rate (Homer *et al.*, 2004b).

Diabetes Onset Rates. One onset (flow) rate is calculated for the progression of the undiagnosed pre-diabetes population to the diabetic stage, and another for diagnosed pre-diabetes patients. Both rates are affected by obesity and age. The average annual onset rate of diabetes for non-elderly and non-obese population is estimated at 1.35% per year, with a coefficient of 2.6 for obese and 1.52 for elderly proportions of the population (Homer *et al.*, 2004b) based on time series of obesity and elderly as previously discussed. For the proportion of pre-diabetics that have their risk factors under control, the risk of developing diabetes conditions is reduced to 58% (Homer *et al.*, 2004b).

Onset Rates of Medical Complications Related to Diabetes. One onset (flow) rate is calculated for the progression of the undiagnosed diabetics population to the medical complications stage, and another for diagnosed diabetics. Both rates are affected by obesity and age. The base onset rate for undiagnosed diabetics is estimated at 7.9% per year. The same rate is assumed for diagnosed diabetics who don't have their chronic disease under control. However for diagnosed diabetics who have their chronic disease under control the rate is reduced to 16% (Homer *et al.*, 2004b).

Diagnosis rates

Pre-diabetes Diagnosis Rate. The "unidentified pre-diabetes" stock and "diagnosed pre-diabetes" stock are interrelated through flow variable "pre-diabetes diagnosis". Pre-diabetes diagnosis flow is the annual rate at which persons with unidentified pre-diabetes are diagnosed and brought under providers' care. The calculation involves a first-order delay (Sterman, 2000) of the pre-diabetes onset flow, with an average delay time equal to 1.5 years, reflecting the median of the typical range of detection (0-3 years) (Homer *et al.*, 2004b). The calculation next subtracts those who have died (*i.e.*, mortality outflows from the stock) or progressed to another stage during the delay. Finally, it applies the prevailing diagnosis fraction for pre-diabetes. The fraction is the product of the fraction of screenings for pre-diabetes and the average sensitivity of the screening test used for pre-diabetes, estimated at coefficients of 0.30 and 0.84 respectively (Genuth *et al.*, 2003; Homer *et al.*, 2004b).

Diabetes Diagnosis Rate. The "unidentified diabetes" stock and "diagnosed diabetes" stock are interrelated through flow variable "diabetes diagnosis" in a similar fashion. Diabetes diagnosis flow is the annual rate at which persons with unidentified diabetes are diagnosed and brought under diabetes care. The diagnosis typically occurs as the result of screening the population with significant risk factors for diabetes. The calculation involves a first-order delay of diabetes onset flow for 1.5 years and subtractions of outflows that occur during the delay, as described in the previous stage, with only the diagnosis fraction changing to reflect screened diabetics (coefficient 0.86, *cf.* Homer *et al.*, 2004b) and sensitivity of screenings specific to diabetics (coefficient 0.60x0.97 + 0.40x0.84). The latter coefficient is estimated based on 60% receiving the more conclusive oral glucose tolerance test (OGTT), which has 97% sensitivity, and the remainder receiving only the fasting plasma glucose test (FPGT), which has a sensitivity of 84% (Harris, 1995; Homer *et al.*, 2004b).

Medical Complications Diagnosis Rate. The "unidentified medical complications" stock and "diagnosed medical complications" stock are interrelated through flow variable "complications diagnosis" in a similar fashion. Complications diagnosis flow is the annual rate at which diabetics who have developed diabetes-related medical complications are diagnosed and brought under providers' care. The diagnosis typically occurs as the result of a physician visit or emergency pertaining to symptoms of medical complications. Because symptoms are more visible, an estimated average of 1.0 years is used for the first-order delay at this stage. Outflows that occur during the delay are subtracted, as described in the previous stages. The diagnosis fraction is a function of the fraction of this population who have ready access to healthcare (86%), the fraction with symptoms severe enough to cause them to seek medical attention (33%), a high proportion receiving OGTT in response to more apparent symptoms (90% proportion x 97% sensitivity) and the remainder receiving FPGT (10% proportion x 84% sensitivity) (Harris, 1995; Homer *et al.*, 2004b).

Pre-diabetes and Diabetes Control Fractions

Patients' control of blood glucose, blood pressure and lipids is considered critical for reducing the incidence of progression from pre-diabetes to diabetes, developments of medical complications due to diabetes, and mortalities from medical complications (Skyler, 2004). Because a diagnosed patient whose conditions and risk factors are not under control is not that different from undiagnosed persons, it is important to identify the fraction that are and are not under control (Homer *et al.*, 2004b). For the population of diagnosed pre-diabetics, the controlled fraction is formulated as the product of two factors: (1) the fraction of hyperglycemic population (people with pre-diabetes) under proper clinical management, and (2) the fraction of those patients who maintain control of their conditions and risk factors. The latter is the output of three contributing factors: (1) the ability to self-monitor one's condition and report any changes to one's healthcare providers, (2) the ability to adopt a

healthy lifestyle favorable for the maintenance of control, and (3) the ability to afford prescribed medications needed for maintaining control. Based on this, we can frame the equation for calculating the controlled fraction of pre-diabetics as follows:

> *"Controlled fraction of managed diabetes population =*
> *(1-Fraction of hyperglycemics who need medications for control) × Ability to adopt healthy lifestyle*
> *+*
> *Fraction of pre-diabetics who need medications for control × Ability to self monitor × (1 - Fraction of Hyperglycemics who need lifestyle change for control if taking medications + Fraction of Hyperglycemics who need lifestyle change for control if taking medications × Ability to adopt healthy lifestyle)".*

The first part of the equation represents conditions for pre-diabetics who control their diabetes risk factors by adopting a healthy life style and diet, estimated at 60%, and a fraction of pre-diabetics that require medications, estimated at 33% (Homer *et al.*, 2004b). The second part of the equation represents the ability of the latter medication-dependent pre-diabetics to self-monitor their medication requirements, estimated at 84%, and the ability of those who require both medication and lifestyle changes, estimated at 33%. The same formula and coefficients apply to diagnosed diabetics and to diabetics diagnosed with medical complications, with the sole exception that the fraction of patients that are medication-dependent rises to 95% (Homer *et al.*, 2004b).

MODEL VALIDATION

The stated model simulates the Canadian population life cycles (*i.e.*, flows) through the stages of diabetes based on the effects of diabetes management factors in Canada as-is. We assume a year as the unit of time. We set all stocks to start from their corresponding values in 1950, the year in which our simulation commences.

Simulation models are validated by comparing the simulated behavior and outputs of the model to the actual behavior of the system in the real world (Sterman, 2000). To this end, we compare the simulated population of Canada from 1950 to 2009 to actual published data (*cf.* http://datafinder.worldbank.org) and from 2010 to 2050 are based on published projections (Bélanger *et al.*, 2005; George *et al.*, 2001). Testing the differences between the two sets of data using paired t-test showed no significant difference ($t=0.265$, $p>0.05$)

We also performed a statistical comparison between published reports of diabetes incidence in the Canadian population throughout the 1990s (Public Health Agency of Canada, 1999) and data from our simulation. A two-tailed comparison of the means shows that data from the simulation do not vary significantly from the published data ($t=2.45$, $p>0.05$). Therefore, the simulation exhibits an acceptable match to the actual behaviors of the system.

DEFINING SCENARIOS

Our basic assumption is that a UHIS that helps to "detect disease early and support compliance with commonly accepted care plans" (Dishman, 2004, p. 35) will mitigate patients' health deterioration and mortality due to the escalation of diabetes (*i.e.*, maintaining better health status) by improving diagnoses and control of patients' risk factors and conditions (ADA, 2003; Testa and Simonson, 1998; Wagner *et al.*, 2001). Because our focus in this paper is on improving diagnosis and control for pre-diabetic and diabetic patients, we will not simulate manipulations to the general (*i.e.*, normoglycemic) population. In accordance with our patient-centered focus, we model the two effects of (i) improved diagnosis, and (ii) improved control rates on the incidences of pre-diabetes, diabetes, medical complications and mortality in the population over time. These two effects are modeled as four scenarios: (#1) as-is (*i.e.*, status quo, 0% improvement), (#2) 5% improvements in diagnosis and control rates, (#3) 10% improvements in diagnosis and control rates, and (#4) 20% improvements in diagnosis and control rates.

The improvements are modeled using "step" variables in the simulation (Sterman, 2000). That is, step variables with the improvements corresponding to each respective scenario are added to the diagnosis and control rates for pre-diabetes, diabetes, and medical complications stages starting in year 2008 of the simulation run. The step variables are listed in Appendix A and elaborated as follows. Specifically, for scenario #2, we increased "step variable for stage 1 diagnosis rate", "step variable for stage 2 diagnosis rate", "step variable for stage 3 diagnosis rate", and "step variable for effective controlled fraction of patients" by 5%. For scenario #3, we increased "step variable for stage 1 diagnosis rate", "step variable for stage 2 diagnosis rate", "step variable for stage 3 diagnosis rate", and "step variable for effective controlled fraction of patients" by 10% each. For scenario #4, we increased "step variable for stage 1 diagnosis rate", "step variable for stage 2 diagnosis rate", "step variable for stage 3 diagnosis rate", and "step variable for effective controlled fraction of patients" by 20% each.

To analyze the effects on patients in the population throughout their life cycle, we ran each scenario from 1950 to 2050, an end date that approximates the average life cycle of Canadians today assuming a life expectancy of 82 years and an average population age of 45 (Bélanger *et al.*, 2005). We expect the incidence of diabetes, diabetes-related complications and mortality in the population to decrease with improvements in diagnosis and control rates.

RESULTS

For each of the four scenarios, the projected population and incidences of pre-diabetes, diabetes, diabetes-related medical complications and mortality as at 2050 are summarized in Table 1, and year over year changes are depicted in Figures 4 to 7 respectively. Results from simulation under the "status quo" scenario project that within the lifespan of the average Canadian today (*i.e.*, 2008-2050) the Canadian population will grow to 42,204,300 people of which 13.421,660 will be pre-diabetic, 2,891,860 will have escalated to diabetes, 580,697 will have diabetes and related medical complications, and a cumulated 21,169,955 mortalities will have occurred.

Under the scenario of 5% improvement in diagnosis and control rates, the incidence of pre-diabetes, diabetes, diabetes-related medical complications and mortality would be 13,197,730, 2,860,000, 568,163 and 21,012,018 respectively within a population of 42,356,800 people. These results represent net benefits of 223,930 fewer pre-diabetics, 31,860 fewer diabetics, 12,534 fewer people escalating to diabetes and related medical complications, and a cumulated 157,937 fewer mortalities versus status quo.

Under the scenario of 10% improvement in diagnosis and control rates, the incidence of pre-diabetes, diabetes, diabetes-related medical complications and mortality would be 12,952,310, 2,823,668, 553,707 and 20,843,106 respectively within a population of 42,519,700 people. These results represent net benefits of 469,350 fewer pre-diabetics, 68,192 fewer diabetics, 26,990 fewer people escalating to diabetes and related medical complications, and a cumulated 326,849 fewer mortalities versus status quo.

Under the scenario of 20% improvement in diagnosis and control rates, the incidence of pre-diabetes, diabetes, diabetes-related medical complications and mortality would be 12,397,440, 2,736,289, 519,448, and 20,475,574 respectively within a population of 42,874,100 people. These results represent net benefits of 1,024,220 fewer pre-diabetics, 155,571 fewer diabetics, 61,249 fewer people escalating to diabetes-related medical complications, and a cumulated 694,381 fewer mortalities versus status quo.

	Projected populations:				
Scenario	Total	Pre-Diabetic	Diabetic	Medical Complications	Mortalities (cumulated)
(#1) Status Quo	42,204,300	13.421,660	2,891,860	580,697	21,169,955
(#2) 5% Improvement	42,356,800	13,197,730	2,860,000	568,163	21,012,018
(#3) 10% Improvement	42,519,700	12,952,310	2,823,668	553,707	20,843,106
(#4) 20% Improvement	42,874,100	12,397,440	2,736,289	519,448	20,475,574

Table 1. Projected populations by scenario as at the year 2050

The results also show that doubling the improvements in diagnosis and control (*i.e.*, from 5% to 10%, or 10% to 20%) more than doubles the beneficial effects over patients' life cycles. Based on these results, we conclude that ubiquitous healthcare information systems that enable better-informed decision-making that improves diagnosis and control of diabetes risks and conditions can be expected to significantly reduce the incidence of pre-diabetes, diabetes and diabetes-related medical complications in the population over the course of patients' life cycles, and significantly reduce the number of mortalities.

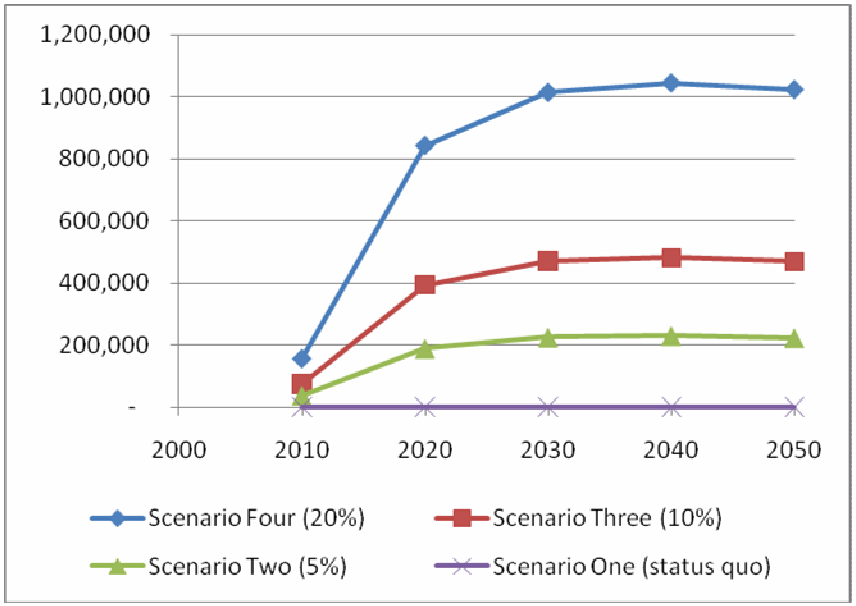

Figure 4. Reduction in annual incidence of pre-diabetes

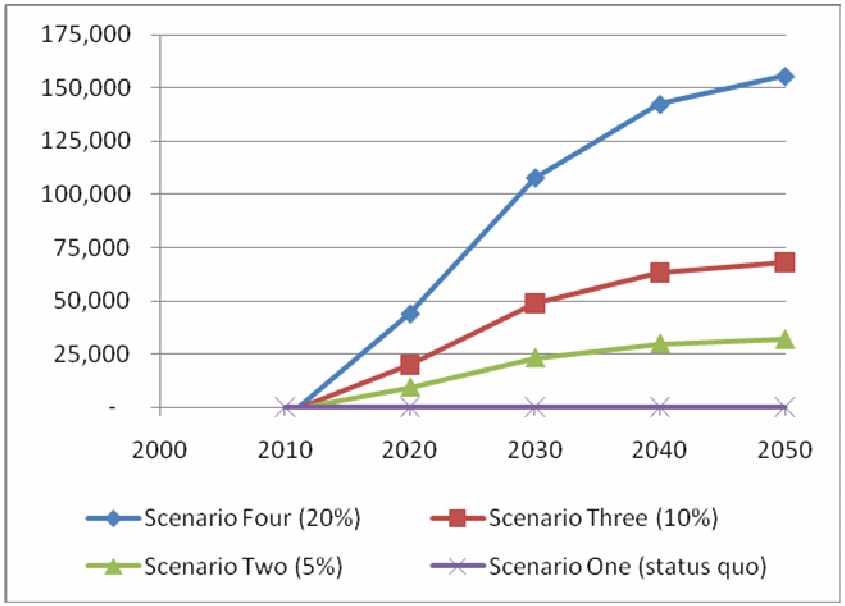

Figure 5. Reduction in annual incidence of diabetes

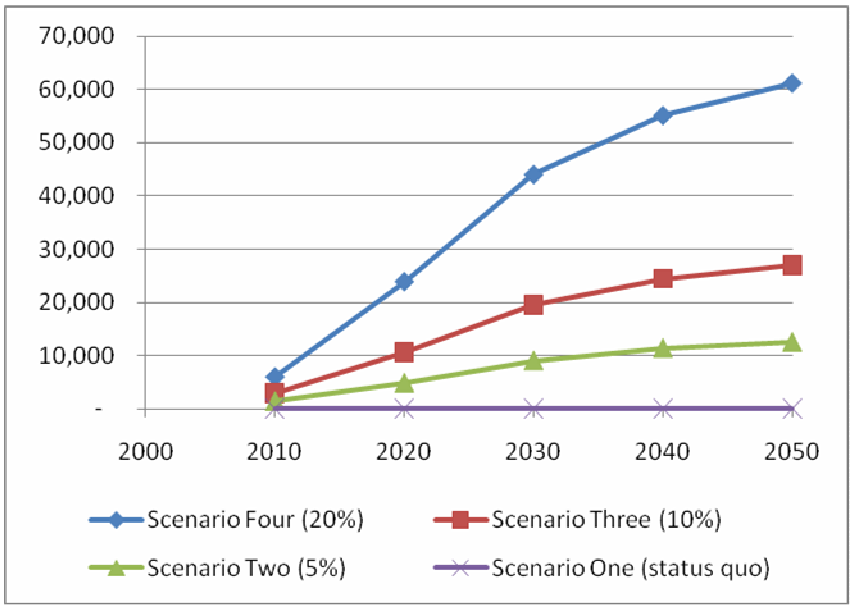

Figure 6. Reduction in annual incidence of diabetes-related medical complications

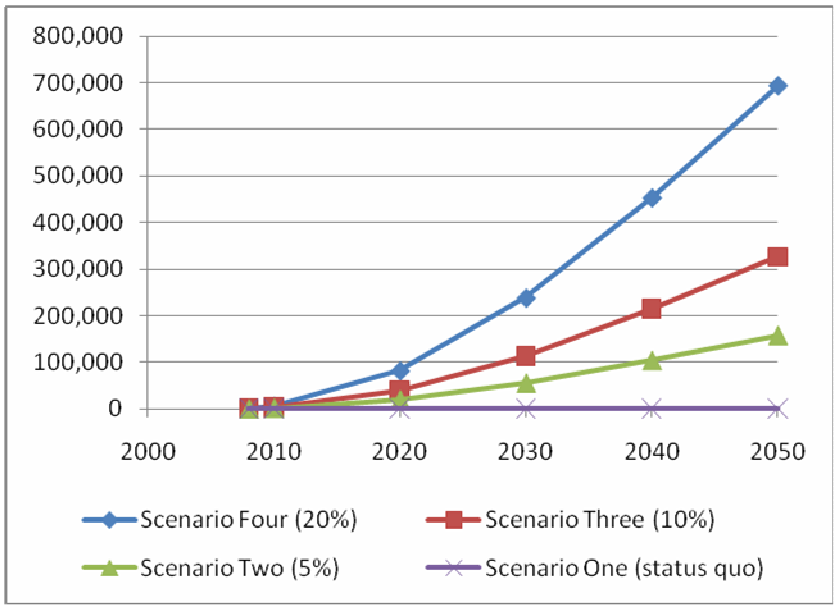

Figure 7. Cumulative reductions in mortalities

CONCLUDING REMARKS

The overarching objective of diabetes management is to mitigate the escalation of patients' conditions and risk factors over time. Diabetes management depends on the participation of patients and the advice of healthcare providers. Consequently, care decisions and treatment depend on the exchange of all information relevant to care decisions among patients and healthcare providers (Bugge *et al.*, 2006). To that end, the literature has advocated the use of UHIS (Korhonen and Bardram, 2004) to help detect medical conditions early and support patients' compliance with treatment plans (Dishman, 2004). However, the significance of patients' health status improvements that would arise from better-informed detection (*i.e.*, diagnosis) and greater compliance is unknown. Our system dynamics model enables policy-makers to assess the impact of UHIS on improved health status of the patients.

There are a number of limitations enforced in this study. This paper presents a limited number of "what if" scenarios (*i.e.*, 5%, 10%, and 20% improvements), applied only to diagnosis and control rates for pre-diabetics and diabetics. The results presented here do not reflect possible improvements to prevention and obesity – a major factor in the escalation of diabetes in the population – in the normoglycemic population that could conceivably result from UHIS that prompts individuals to increase their exercise for instance (*e.g.*, Korhonen and Bardram, 2004). The results do not illustrate the effects of earlier diagnosis (*i.e.*, we improved the proportion or rate of successful diagnoses while retaining the "as-is" time lag for diagnosis) that could conceivably result from healthcare providers being alerted by real-time monitoring of patients' biological conditions or identifying at-risk individuals with the aid of data mining systems (*e.g.*, Bonato, 2003). The results do not reflect potential operational benefits that could conceivably arise from automated data gathering of patients' biological conditions, real-time alerts that enable proactive rather than reactive responses to emergencies such as cardiovascular events, and more efficient decision-support made possible by data mining systems that analyze UHIS data (*e.g.*, Bonato, 2003). Nor do the results reflect potential benefits with respect to other diseases that could conceivably arise from better compliance with practices, such as increased exercise, as a result of UHIS.

Nonetheless, we find that improved diagnosis and control afforded by UHIS has the potential to provide (i) a significant improvement in patients' health status arising from significantly less deterioration of health throughout patients' life cycles, and (ii) a significant reduction of mortalities. Therefore, the health status improvements presented in this paper should be interpreted as the *minimum benefits* that decision-makers may expect from better-informed decisions and improved diagnosis and control made possible through the application of UHIS in support of a patient-centered care approach to diabetes management. Future research can expand our model to include the following enhancements: (1) potential benefits of improved preventative care afforded by pervasive consumer technologies that monitor factors such as diet, exercise and obesity, (2) the effects of earlier diagnoses, and (3) operational efficiencies that could result from patient-centered information systems, such as automated recordkeeping and real-time diagnoses.

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APPENDIX A – VARIABLES USED IN MODEL

Variable Name	Definition
Stock Variables	
Canadian Normoglycemic Population	Canadian population with normal level of blood sugar
Unidentified Population of Stage 1 Patients	Canadian population with pre-diabetes indications who have NOT been diagnosed, yet.
Diagnosed Population of Stage 1 Patients	Canadian population with pre-diabetes indications who have been diagnosed with pre-diabetes indications.

Unidentified Population of Stage 2 Patients	Canadian population with diabetes without complications whose chronic disease have NOT been diagnosed, yet.
Diagnosed Population of Stage 2 Patients	Canadian population with diabetes without complications whose chronic illness have been diagnosed.
Unidentified Population of Stage 3 Patients	Canadian diabetics with medical complications whose chronic disease have NOT been diagnosed, yet.
Diagnosed Population of Stage 3 Patients	Canadian diabetics with medical complications whose chronic disease have been diagnosed.
Flow Variables	
Population Inflow	Yearly-based net increase in Canadian population (excluding the effect of death).
Normoglycemic death rate	Yearly-based death rate of population with normal blood sugar level.
Onset rate for pre-diabetes	Yearly-based rate of pre-diabetes onset for normoglycemic population (from normoglycemic stage to unidentified pre-diabetes stage).
Recovery from unidentified stage 1	Yearly-based rate at which unidentified pre-diabetics are recovered (i.e. become normoglycemic).
Unidentified stage 1 death rate	Yearly-based death rate of pre-diabetics (i.e. as pre-diabetes doesn't affect the patient's death, it is equal to normoglycemic death rate).
Progression rate from unidentified stage 1 to unidentified stage 2	Yearly-based rate at which unidentified pre-diabetics' illness is progressed to chronic diabetes (i.e. stage 2) which is not diagnosed.
Diagnosis rate for stage 1 patients	Yearly-based rate at which the unidentified pre-diabetics are diagnosed as having pre-diabetes.
Recovery from diagnosed stage 1	Yearly-based rate at which pre-diabetics whose illness is diagnosed are recovered (i.e. become normoglycemic).
Diagnosed stage 1 death rate	Yearly-based death rate of pre-diabetics (i.e. as pre-diabetes doesn't affect the patient's death, it is equal to normoglycemic death rate).
Progression rate from diagnosed stage 1 to diagnosed stage 2	Yearly-based rate at which diagnosed pre-diabetics' illness is progressed to chronic diabetes (i.e. stage 2) and this progression is also diagnosed.
Unidentified stage 2 death rate	Yearly-based death rate of unidentified diabetics without medical complications.
Progression rate from unidentified stage 2 to unidentified stage 3	Yearly-based rate at which unidentified diabetics' illness (i.e. without medical complications) is progressed to diabetes with medical complications and this progression is not diagnosed.
Diagnosis rate for stage 2 patients	Yearly-based rate at which the unidentified diabetics without medical complications are diagnosed.
Diagnosed stage 2 death rate	Yearly-based death rate of diagnosed diabetics without medical complications.
Progression rate from diagnosed	Yearly-based rate at which diagnosed diabetics' illness (i.e. without

stage 2 to diagnosed stage 3	medical complications) is progressed to diabetes with medical complications and this progression is also diagnosed.
Death rate for Unidentified stage 3 patients	Yearly-based death rate of unidentified diabetics with medical complications.
Diagnosis rate for stage 3 patients	Yearly-based rate at which the unidentified diabetics with medical complications are diagnosed.
Death rate for diagnosed stage 3 patients	Yearly-based death rate of diagnosed diabetics with medical complications.
Auxiliary Variables	
Population death rate	Time series of Canadian population death rate from 1950 to 2050.
Net population growth	Yearly-based net difference in the number of Canadian population.
Obese Fraction	Time series of fraction of obese population in Canada from 1950 to 2050.
Elderly portion	Time series of portion of elderly population (+65) in Canada from 1950 to 2050.
Ave. time from S1 onset to detection for undx hypreglycemic	Average time from symptoms onset for an unidentified pre-diabetic to when she is diagnosed by the medical doctor.
Dx fraction of recent undx S1 onset	The fraction of unidentified pre-diabetics who are diagnosed, each year.
Ave. time from S2 incidence to detection for undx hypreglycemic	Average time from symptoms onset for an unidentified diabetic without medical complications to when she is diagnosed by the medical doctor.
Dx fraction of recent undx S2 onset	The fraction of unidentified diabetics without medical complications who are diagnosed with the disease, each year.
Ave. time from S3 incidence to detection for undx hypreglycemic	Average time from symptoms onset for an unidentified diabetic with medical complications to when she is diagnosed by the medical doctor.
Dx fraction of recent undx S3 onset	The fraction of unidentified diabetics with medical complications who are diagnosed with the disease, each year.
Fraction of diagnosed receiving effective care	Fraction of patients with diagnosed illness who are receiving effective care (i.e. effective in decreasing the progression of the disease) based on: 1) Their ability to adopt a healthy lifestyle, 2) Their ability to self-monitor themselves, and 3) their ability to afford the required medications.
Controlled fraction coefficient for S1	Fraction of diagnosed pre-diabetics whose health problem is controlled (i.e. its progression is delayed or stopped).
Controlled fraction coefficient for S2 and S3	Fraction of diagnosed diabetics whose health problem is controlled (i.e. its progression is delayed or stopped).
Auxiliary Variables for Manipulation ("Step Variables")	
Step variable for stage1	Step variable for inducing the improvements to the diagnosis rate of

diagnosis rate	unidentified pre-diabetics (i.e. Stage 1).
Step variable for stage2 diagnosis rate	Step variable for inducing the improvements to the diagnosis rate of unidentified diabetics without medical complications (i.e. Stage 2).
Step variable for stage3 diagnosis rate	Step variable for inducing the improvements to the diagnosis rate of unidentified diabetics with medical complications (i.e. Stage 3).
Step variable for Effective Controlled Fraction of patients	Step variable for inducing the improvements to the control rate for diagnosed patients (i.e. for controlled fraction of diagnosed patients in all stages).

Table 2. Simulation variables and their definitions, adapted from Homer *et al.*, (2004b)