# A Systems Engineering Framework for Multi-Criteria Performance Evaluation of Healthcare Process and Systems

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## Extended Abstract

### *1. Introduction and Description of the Problem and Goals*

Health expenditures for diabetes and its complications totals 376 billion dollar (USD) and is expected to exceed 490 USD billion by 2030. Developed world countries count for 80% and US for 52% of these total health expenditures. ***Type 2 diabetes*** is a chronic disease with long term complications as blindness, renal failure and increased risk for stroke and myocardial infraction. There are several studies related to prediction of diabetes type 2. Most famous models and widely used are the IRIC, QDScore, DESIR. All models seek to be aligned with age, BMI and waist circumference as variables, however, the performance of each model varies between countries, age, sex, and adiposity. One of the methods that have been used in the past to define the risks and performance of several treatments for diabetes type 2, is Markov chain models constructed for a heterogeneous subscriber population, and used to examine the long-run effects of particular utilization patterns on disease functioning.

Systems Engineering (SE) is an approach combining the advantage of model-based systems descriptions, based on modular components, integrated with sophisticated tradeoff analysis and design space exploration, to design and analyze the performance of complex systems in many domains, ranging from engineering, to economics, to enterprises, and most recently to healthcare systems and processes [17]. In fact, the recent PCAST report [17] recommends SE as a critical methodology for accelerating improvements in healthcare systems towards higher quality and lower costs. However, there are very few studies using this modern and interdisciplinary approach to healthcare. The present paper describes our research towards developing such a framework for the case of diabetes type 2, that will allow all stakeholders of healthcare to assess the benefits of specific policies, technologies, treatments etc., with

respect to several metrics, including economic metrics. Further we propose that modern SE methodologies are uniquely capable to evaluate the interrelationships between healthcare, information technology and economics. We offer the present study as a prototypical example.

The purpose of the present study is to classify population groups based on diabetic risk, formulate models of structure and behavior, set requirements for treatment performance and construct states (for various relevant processes, including the disease, patients, treatments, technologies). Every state will have different probabilities of disease progression, cost function and health performance. Finally, the results of every state will be used to construct and validate the Markov chain model. From the Markov chain model, for every step, outputs of the model will be total cost, risk, health performance. Also every state will generate a different sum total of cost, health performance and risk. Every state shows different progression of the disease that will need different cost function (combination of treatment and medicine), health function (Qaly). Each step represents the evolution (progression) of the model through time.

## *2. Methodology*

The model is influenced from the Archimedes, Michigan, UKPDS and Desir models. We are incorporating the advantages from every model and we integrate them into a new system that is more complete and detailed. There are several ***classes*** that interact among them (see Fig. 3). The classes of the system are people, facilities, records, interventions, equipment, supplies and budget. Each class has attributes; e.g. in the case of people they have organs, which have also inside them parts and subparts, like the heart that has parts of coronary, arteries, etc.

Figures 1 and 2 show the basic algorithm and a typical flowchart (for a specific path of the disease) employed in our model. Figure 1 shows the various input parameters and the output from the model. There are many variations of the model and algorithms that can be used; we just show a typical example here. For diabetes type 2, disease is indicated by a test result of >125 mg/dl glucose level in blood in the FPG test, or >199 mg/dl glucose level in blood in OGTT test. A tool that capture the information that someone has a disease is a *diagnostic test*, or *screening test*, or *monitoring test*.

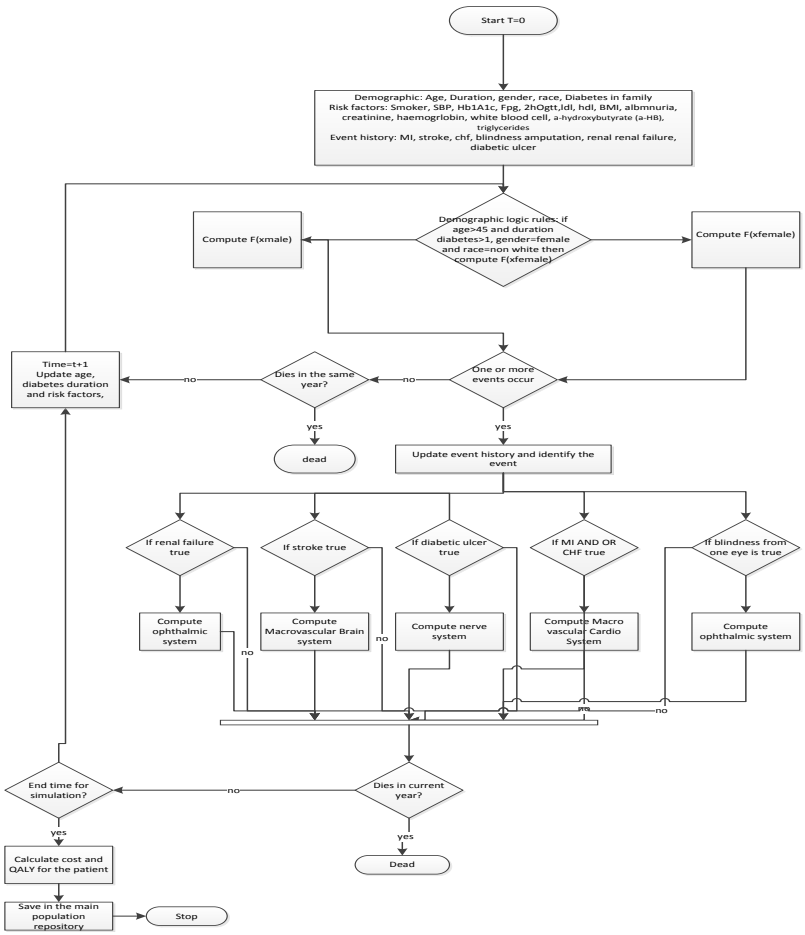


**Fig. 1:** Basic algorithm in the model

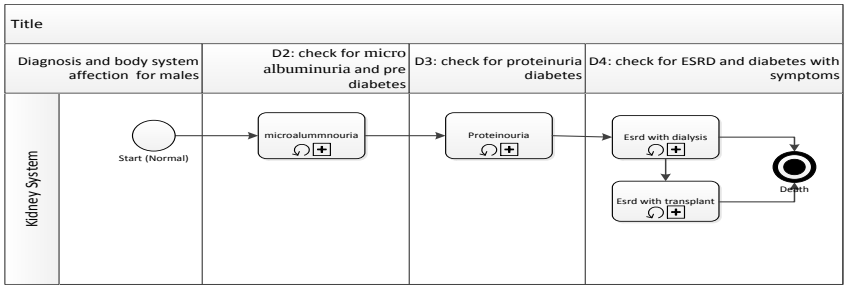


**Fig. 2**: Flowchart of kidney system related to neuropathy and renal failure.

### *3. Computation of the risk for every gender*

An important part of our model is the computation of risk from various input parameters of the model as shown below in an example.

$$\begin{Bmatrix} 0 = male, f(x_m) = -10.45 + 0.94Sm + 0.06\,Wc + 10.17\,Fpg + 22.42\,Ogtt + 0.42Ggt + 0.14Omic \\ 1 = female, f(x_f) = -20.43 + 0.75Df + 4.69\,Bmi + 9.35\,Fpg + 22.39\,Ogtt + 0.86\,Trg + 0.36Omic \end{Bmatrix}$$

Where SM= smoker, Wc= Waist circumference, FPG= fast plasma glucose test, 2Ogtt= 2 hours fast plasma test, GGT= Gama Glutamyl Transpeptidase, Omic= creatine blood test, Df= family diabetic history, BMI= body mass index, Trg= Triglycerides

Figure 3 illustrates a simple example of classes involved in the model and transitions between classes. A key issue with this type of models is the very large number of states they may require. We have developed methods to handle this complexity in our earlier work. For example, we have $3^N$ states, corresponding to the ***normal/prediabetic/diabetic*** status of each patient. When screen is in the normal state, if there is a ***prediabetic risk*** the patient status is switched to ***prediabetic***. Otherwise the status goes to ***normal or diabetic*** patient. When a patient occupying a bed is in the ***normal*** state, the status of the patient is switched to ***normal***. Beds have their own three state variables, reflecting the patient state for each bed, but these do not directly alter the state of the risk machines. Due to space limitations we do not provide more details of the model, other than these examples.

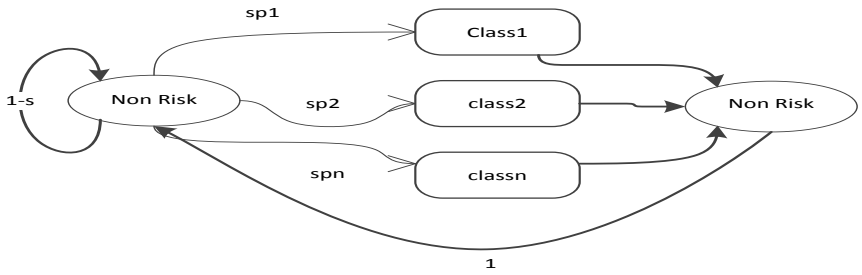


**Fig. 2**: Illustrating classes and transitions between classes linked to risk .

### *4. Resource Model and Cost*

Our model includes a resource and cost model. In [Unerti, 2009] the cost is described for the staff that will be needed for a diabetic clinic as a dependent variable, on the disease screening and consultation in the following manner. The cost of every part depends on the cost per hour for every specialty, the cost of every software or web application used, the cost of telemedicine equipment, the cost of the tests that will be needed in every point of screening. The stationary screening distribution can be computed from patient states. Each occupancy level is associated with a cost based on the above so expected cost can be

computed from the state distribution. The resource model can depend on several other parameters. The entire model is linked with tradeoff analysis tools based on multi-metric optimization.

### *References*


1. American Diabetes Association Consensus Panel: Guidelines for computer modeling of diabetes and its complications (Consensus Statement). *Diabetes Care* **27**: 2262–2265, 2004
2. Stevens RJ, Kothari V, Adler AI, Stratton IM, Holman RR: The UKPDS risk engine: a model for the risk of coronary heart disease in type II diabetes (UKPDS 56). *Clin Sci (Lond* )**101**:671–679, 2001
3. Zhou H, Isaman DJ, Messinger S, et al. A computer simulation model of diabetes progression, quality of life, and cost. Diabetes Care. 2005 Dec;28(12:2856-63. PubMed PMID: 16306545.
4. Stevens RJ, Coleman RL, Adler AI, Stratton IM, et al: Risk factors for myocardial infarction case fatality and stroke case fatality in type 2 diabetes: UKPDS 66. *Diabetes Care* **27**:201–207, 2004
5. Adler AI, Stevens RJ, Manley SE, et al: Development and progression of nephropathy in type 2 diabetes: the United Kingdom Prospective Diabetes Study (UKPDS 64). *Kidney Int***63**:225–232, 2003
6. Stratton IM, Kohner EM, Aldington SJ, et al: UKPDS 50: risk factors for incidence and progression of retinopathy in type II diabetes over 6 years from diagnosis. *Diabetologia***44**:156–163, 2001
7. Müller E, Maxion-Bergemann S, et al: EAGLE Diabetes Model: basic features and internal validation of simulating long-term diabetic outcomes and related costs (Abstract). *Value Health***7**:745, 2004
8. Müller E, et al: EAGLE–Economic Assessment of Glycemic control and Longterm Effects: a computer simulation model for diabetes mellitus type 1 and type 2. *Diabetologia* **47**:A355, 2004
9. Mueller E, et al: Development and validation of the Economic Assessment of Glycemic Control and Long-Term Effects of diabetes (EAGLE) model. *Diabetes Technol Ther* **8**:219–236,2006
10. J.S. Baras, et al; Compositional Analysis of Dynamic Bayesian Networks and Applications to Complex Dynamic System Decomposition, Procedia Comp. Science, Vol 16, 167-176, 2013
11. Hayes AJ, Leal J, Gray AM, Holman RR, Clarke PM. UKPDS outcomes model 2: a new version of a model to simulate lifetime health outcomes of patients with type 2 diabetes mellitus using data from the 30 year United Kingdom Prospective Diabetes Study: UKPDS 82. Diabetologia. 2013 Sep;56(9):1925-33. doi: 10.1007/s00125-013-2940-y. Epub 2013 Jun 22. PubMed PMID: 23793713
12. Zhang P, Zhang X, Brown J, Vistisen D, et al. Global healthcare expenditure on diabetes for 2010 and 2030. Diabetes Res Clin Pract. 2010 Mar;87(3):293-301. doi: 10.1016/j.diabres.2010.01.026. Epub 2010 Feb 19. Erratum in: Diabetes Res Clin Pract. 2011 May;92(2):301. PubMed PMID: 20171754.
13. Schmidt MI, Duncan BB, Bang H, Pankow JS, Ballantyne CM, et al; Atherosclerosis Risk in Communities Investigators. Identifying individuals at high risk for diabetes: The Atherosclerosis Risk in Communities study.Diabetes Care. 2005 Aug;28(8):2013-8. PubMed PMID: 16043747.
14. Unerty KM, Weinger MB, et al; Describing and modeling workflow and information flow in chronic disease care. J Am Med Inform Assoc. 2009 Nov-Dec;16(6):826-36. doi: 10.1197/jamia.M3000. Epub 2009 Aug 28. PubMed PMID: 19717802; PubMed Central PMCID: PMC3002133.
15. Vaxillaire M, et al; DESIR Study Group. The common P446L polymorphism in GCKR inversely modulates fasting glucose and triglyceride levels and reduces type 2 diabetes risk in the DESIR prospective general French population. Diabetes. 2008 Aug;57(8):2253-7. doi: 10.2337/db07-1807. Epub 2008 Jun 12. PubMed PMID: 18556336; PubMed Central PMCID: PMC2494697.
16. Jaziri R, et al; DESIR Study Group. The PPARG Pro12Ala polymorphism is associated with a decreased risk of developing hyperglycemia over 6 years and combines with the effect of the APM1 G-11391A single nucleotide polymorphism: the Data From an Epidemiological Study on the Insulin Resistance Syndrome (DESIR) study. Diabetes. 2006 Apr;55(4):1157-62. PubMed PMID: 16567542
17. REPORT TO THE PRESIDENT, "BETTER HEALTH CARE AND LOWER COSTS: ACCELERATING IMPROVEMENT THROUGH SYSTEMS ENGINEERING," Executive Office of the President, President's Council of Advisors on Science and Technology (PCAST), May 2014.