

5-15-2014

An Analytics Approach to Managing Provider Treatment Variety to Improve Patient Outcomes for a Type-2 Diabetes Clinic

Gregory Ramsey

Morgan State University, gregory.ramsey@morgan.edu

Ashish Gupta

University of Tennessee Chattanooga, gupta@utc.edu

Youngok Kwon

Sookmyung Women's University, youngok.kwon@gmail.com

Follow this and additional works at: <http://aisel.aisnet.org/mwais2014>

Recommended Citation

Ramsey, Gregory; Gupta, Ashish; and Kwon, Youngok, "An Analytics Approach to Managing Provider Treatment Variety to Improve Patient Outcomes for a Type-2 Diabetes Clinic" (2014). *MWAIS 2014 Proceedings*. 2.

<http://aisel.aisnet.org/mwais2014/2>

This material is brought to you by the Midwest (MWAIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in MWAIS 2014 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

An Analytics Approach to Managing Provider Treatment Variety to Improve Patient Outcomes for a Type-2 Diabetes Clinic

Gregory Ramsey
Morgan State University
gregory.ramsey@morgan.edu

Ashish Gupta
University of Tennessee Chattanooga
gupta@utc.edu

YoungOk Kwon
Sookmyung Women's University
youngok.kwon@gmail.com

Abstract

This study investigates an analytics approach to improving clinical outcomes, which is to utilize EHR data to identify and exploit variety of successful treatments that physicians deliver for different types of patients. A simulated environment was used to develop and test the proposed approach that assigns patients to physicians for better treatment of type-2 diabetes in a clinic setting. Results from this study demonstrate a 30% increase in patients being successfully brought to A1c goal, a 30-fold decrease in treatment errors, and a 12% decrease in outpatient costs to treat patients compared to traditional treatment procedures in diabetes clinic. These techniques can be integrated with EHR systems, thus helping hospitals meet Stage 3 meaningful-use requirements for improving patient outcomes.

Keywords: Analytics, EHR, patient-provider matching, recommendation systems.

1. INTRODUCTION AND MOTIVATION

Recent healthcare reforms have led to the Health Information Technology for Economic and Clinical Health Act (HITECH) that requires health providers to use EHR in meaningful ways [1]. The definition of “meaningful” has been intensely discussed and debated. The intent behind the meaningful-use mandate is to improve the safety, quality, and efficiency of care through the use of EHRs [1]. What is now the focus of much research and study is identifying, developing, and implementing ways of achieving *meaningful use*.

This study examines a novel application of analytics to Electronic Health Records (EHR) for improving clinical outcomes by intelligently matching patients with physicians. New public health policies are being developed to support healthcare reform in the United States, with particular emphasis being placed on accessibility of care for all [2]. An often discussed issue is how best to deliver care to the masses. A frequently proposed solution is to use clinical settings where patients receive the bulk of their care from a pool of primary care physicians associated with a specific clinic [3, 4]. This being the dominant means for care delivery where that new patients are typically assigned to a physician based on availability during the initial visit [5, 6]. Such an approach comes with major drawback in terms of mismatch between the provider skills and patient requirements. Therefore, the key research question that is investigated in this study is, “how can initial matches between physicians and patients be made so as to improve outcomes over the longevity of care within a clinical environment?” Specifically, this study focuses on matching patients to physicians for the treatment of chronic disease. Type-2 diabetes is the chronic disease examined in the current study.

We also propose a framework for integrating the predictive models with the existing EHR systems in the clinical environment. This framework also guides the development of the approach that improves patient's assignment to primary care physicians for better clinical outcomes. The results of this study provide a basis for designing better clinical decision support functionalities within an EHR to help satisfy requirements for Stage 3 Meaningful-Use [7]. Furthermore, this research contributes to the medical decision-making and the broader DSS bodies of knowledge by introducing a novel way of applying analytics to dynamically define performance-based constraints for developing better next-generation recommendation systems or solving complex assignment problems in clinical settings.

2. RELATED WORK

Currently, the majority of research in the area of matching patients and providers of care focuses on improving either economic or operational assets. For example, Bynum et al. [8] examined retrospective methods of matching patients with physicians who were in turn matched to specific hospitals. Similarly, Pham et al. [9] performed a retrospective study of patients treated by physicians comparing algorithms for crediting individual providers with treatment outcomes. Studies complementary to these on matching patient and providers have focused on analyzing and prescribing ways of changing provider behavior, with respect to better patient education, to produce better clinical outcomes [10]. Unfortunately, a major limitation to these types of studies is that the prescribed changes in behavior are often temporary, if at all [11], and therefore does not lead to a permanent solution to this problem.

Both approaches have limitations and there is a significant gap that can be filled by conducting studies that a) account for individual differences among provider's skills and expertise, b) prescribe a solution that dynamically adapts to the real time medical data stored within EHRs, c) is usable by the clinical environment.

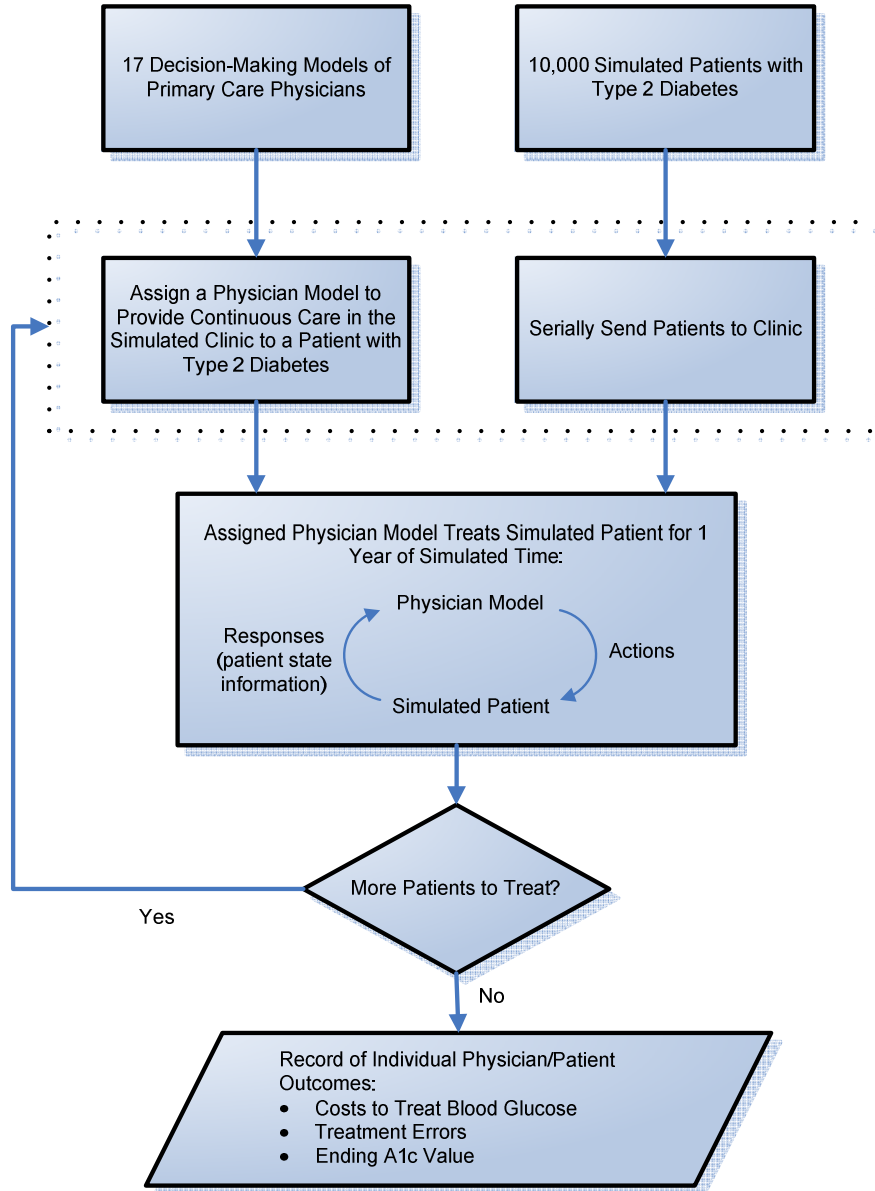
Diabetes Management

Type 2 diabetes is a disease where a person is unable to produce sufficient quantities of insulin to maintain control of blood glucose levels within their body [12]. Type 2 diabetes is a chronic disease that can be controlled, but not cured. Consequently physicians treating this disease engage in a process control task with an objective of bringing patients to clinical goals for blood glucose levels while simultaneously managing comorbidities (such as hypertension and dyslipidemia). As the disease progresses control of blood glucose levels typically requires a progression in treatments. Treating a type 2 diabetes patient entails scheduling regular visits for assessing patient conditions and taking actions to affect patient states [13]. Associated with these visits physicians have to gather information on the patient's state either via laboratory test or patient self-reports. Based on information gathered and clinical goals a physician can take treatment actions.

3. CONCEPTUAL FRAMEWORK

This study used Ashby's Law of Requisite Variety as the basis for matching a patient with a healthcare provider for a given visit. The law states that only variety of control actions can destroy the variety of outcomes [14]. Figure 1 describes the proposed framework for managing the provider-patient variety, which also guides the development of the simulated clinic described in the subsequent section.

Figure 1: Conceptual Foundation for the Analytics Driven Patient-Provider Matching System



3. The simulated Diabetes Clinic

The simulated diabetes clinic consists of different physician models treating patients on an individual basis. A simulated clinic comprised of models of patients with type 2 diabetes (T2DM) and models of physician decision-making processes. The physician and patient models were developed and tested in prior studies [15, 16].

The physician models are agents that compute actions to be taken based on the information received from the simulated patient being treated. The physician models take actions to measure patient states via simulated diagnostic tests (e.g., measuring blood glucose levels via self-monitoring blood glucose or HgbA1c tests), to prescribe medications for altering the blood glucose levels, and to schedule visits with the patient to create opportunities for taking further actions with the patient. Each physician model comprises of a rule set that is used to process information for making decisions and taking action. Accompanying this rule set is a knowledge base that contains knowledge that a physician model has access to for guiding their decision-making process and treatment

actions. The patient model developed within the simulated clinic comprises of a separate rule set for determining a patient’s time-dependent responses to medication treatment actions taken. Medication actions exhibit time delays before affecting blood glucose levels within the patient and these time dependencies are based on published dose-response curves for insulin and oral agents [16, 17].

Outcomes of the simulations were evaluated according to three metrics: errors, patient blood glucose outcomes, and cost to treat blood glucose. Errors were scored as any action that a physician took with a patient that did not conform with the published guidelines for treating type 2 diabetes. [13, 18]. Patient blood glucose outcomes were measured by a simulated HgbA1c (abbreviated as A1c) test, which is a 90-day moving average of a patient’s plasma glucose and is a stable means for measuring control of blood glucose levels. The clinical goal for A1c is 7% (but not lower than 4%). Cost to treat blood glucose included costs for office visits, referrals to health professionals, medications, laboratory tests, syringes, and testing supplies.

4. Empirical Results

A patient from the 10,000 simulated patients can be treated by no more than 17 physicians and a total of 169,810 cases are used in our computational experiment. We then develop an analytics based algorithm that provides a recommendation on which physician a patient should be treated depending on the treatment data of the training patients and evaluate the algorithm using the data of the test patients. More specifically, we take the following three steps: (1) clustering training patients into groups based on their initial states, (2) choosing the best physicians for each cluster of patients, and (3) evaluating the physician-patient assignments using test patients.

4.1 Clustering patients based on their initial states

We obtained 7 distinct groups of patients with similar initial conditions. The basic information of each variable used for clustering the training patients and the importance of each variable attributed to the clusters are summarized in Table 1.

Table 1: Variables for each patient’s initial state

Variable Name	Min	Max	Mean	Std. Dev	Importance
Sulf Allergy	0	1	0.154	0.361	0
A1c	4.1	14.9	7.236	1.522	0.517
Adherence	0.26	1	0.870	0.129	0.679
Creatinine	1	1.67	1.350	0.091	1
Insulin	0	68	6.345	11.984	0.847
Glipizide	0	20	4.124	6.336	0
Metformin	0	2000	625.710	815.130	0.235
Pioglitazone	0	45	3.701	10.887	0.539

The properties of the given 7 clusters are described in Table 2. Majority of patients are assigned to only a few clusters. For example, more than half of the training patients belong to Clusters 3 and 7. Patients in Cluster 7 also show the highest success rate in their treatments.

Table 2: Characteristics of clusters (*: many on insulin, **: insulin dose adjustments required)

Cluster	Frequency (Success Rate)	A1c	Creatinine	Initial Meds				Initial A1c Distribution		
				Adherence	Metformin	Pioglitazone	Insulin	H	M	L
1	242 (65.29%)	L	H	0.88	L	H	M	2%	16%	82%
2	648 (70.52%)	L	H	0.59	L	L	L	0%	12%	88%
3	2,468 (65.72%)	L	H	0.91	M	L	L	1%	12%	87%
4	964 (57.05%)	M	M	0.90	L	L	H*	8%	34%	58%
5	310 (22.90%)	H	H	0.77	L	L	L	81%	19%	0%
6	402 (50.75%)	M	H	0.89	H	M	L**	13%	29%	58%
7	1,966 (77.26%)	L	M	0.91	L	L	L	1%	14%	85%

4.2 Choosing the best physicians in each cluster

Once a patient is assigned to one of 7 groups, the patient can choose the most successful treatment actions (i.e., physician model) for the best outcomes. The decision on the most successful physician model is made based on two matching criteria: success rate of a physician in the treatments of patients in a given group and cost for a physician’s treatment. To understand the successful physician’s treatment actions, we performed decision tree analyses and identified some of treatment actions in each cluster. For example, with 99.3% success rate, physicians in cluster 1 showed the following three characteristics of treatments over the course of multiple visits for 1 year.

4.3 Evaluating the success rate of the matched assignments and random assignments

We then evaluate the proposed patient-physician assignments by comparing their outcomes with the ones of random assignments. Figure 2 shows the proportion of patients successfully treated by the matched physician and the randomly assigned physician with different panel sizes. Results demonstrate that an increase in the limit on the patients that a physician can treat does not help the performance of the random assignments.

Finally, we compare the work load of physicians in the two assignments and the results in Figure 3 show that almost every physician is fully engaged in treating patients in the random assignment, whereas the matched assignment decreased the work load up to about 30%, meaning that patients are skewed to a few highly ranked physicians.

Figure 2: Treatment success rate for varying panel sizes.

Notation: Solid lines show proportions of patients successfully treated. Dashed lines show the proportion of the 17 models that were actively engaged in treating patients (an indication of work load balancing).

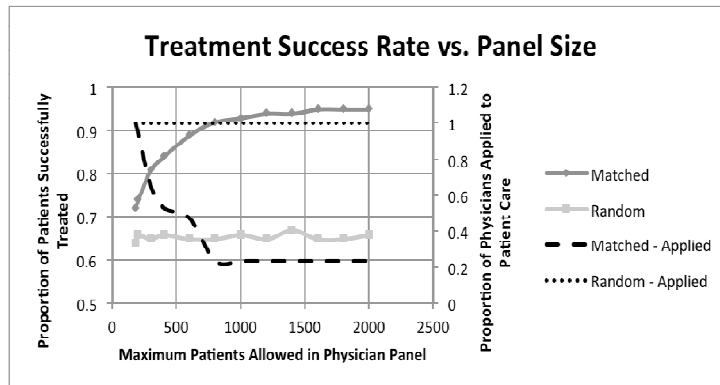
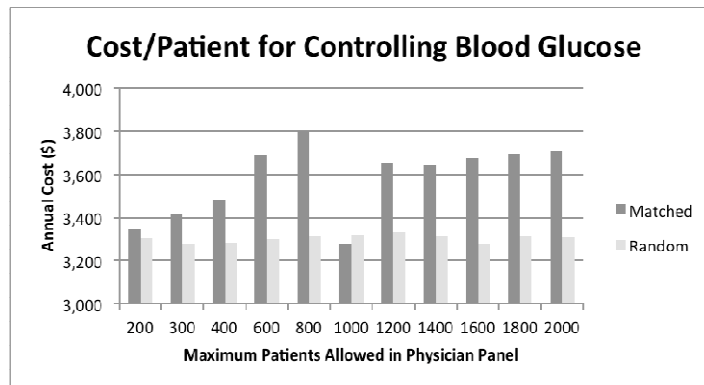


Figure 3: The cost per patient per year to control blood glucose levels (these figures do not include cost for treat comorbidities or any other medical conditions).



REFERENCES

1. Blumenthal, D. and M. Tavenner, *The “Meaningful Use” Regulation for Electronic Health Records*. New England Journal of Medicine, 2010. **363**(6): p. 501-504.
2. Kocher, R., E.J. Emanuel, and N.-A.M. DeParle, *The Affordable Care Act and the future of clinical medicine: the opportunities and challenges*. Annals of Internal Medicine, 2010. **153**(8): p. 536-539.
3. Rittenhouse, D.R., S.M. Shortell, and E.S. Fisher, *Primary Care and Accountable Care — Two Essential Elements of Delivery-System Reform*. New England Journal of Medicine, 2009. **361**(24): p. 2301-2303.
4. Adashi, E.Y., H.J. Geiger, and M.D. Fine, *Health Care Reform and Primary Care — The Growing Importance of the Community Health Center*. New England Journal of Medicine, 2010. **362**(22): p. 2047-2050.
5. Green, L.V., S. Savin, and Y. Lu, *Primary care physician shortages could be eliminated through use of teams, nonphysicians, and electronic communication*. Health Affairs, 2013. **32**(1): p. 11-19.
6. Carrier, E.R., T. Yee, and L. Stark, *Matching supply to demand: addressing the US primary care workforce shortage*. Looking Ahead, 2011. **5**: p. 4.
7. DHHS, *Federal Register*, 2010, National Archives and Records Administration. p. 44321-44328.
8. Bynum, J.P.W., et al., *Assigning Ambulatory Patients and Their Physicians to Hospitals: A Method for Obtaining Population-Based Provider Performance Measurements*. Health Services Research, 2007. **42**(1p1): p. 45-62.
9. Pham, H.H., et al., *Care patterns in Medicare and their implications for pay for performance*. New England Journal of Medicine, 2007. **356**(11): p. 1130-1139.
10. Conn, V.S., et al., *Meta-analysis of patient education interventions to increase physical activity among chronically ill adults*. Patient Education and Counseling, 2008. **70**(2): p. 157-172.
11. Webb, T.L. and P. Sheeran, *Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence*. Psychological Bulletin, 2006. **132**(2): p. 249-268.
12. Guven, S., J. Kuenzi, and G. Matfin, *Diabetes Mellitus and the Metabolic Syndrome*, in *Pathophysiology: Concepts of Altered Health States*, C.M. Porth, Editor. 2005, Lippincott Williams & Wilkins: Philadelphia.
13. Mazze, R., et al., *Staged Diabetes Management: A Systematic Approach, 2nd Edition*. 2nd ed. International Diabetes Center. 2005, Hoboken, NJ: John Wiley & Son.
14. Ashby, W.R., *Variety, Constraint, and the Law of Requisite Variety*, in *Modern Systems Research for the Behavioral Scientist*, W. Buckley, Editor. 1968, Aldine Press: Chicago. p. 129-136.
15. Ramsey, G., *Success and Failure in Dynamic Decision Envrionments: Understanding Treatment Strategies for Patients with a Chronic Disease*, in *The Carlson School of Management* 2010, University of Minnesota: Minneapolis.
16. McCabe, R.M., *Validating a Computational Model of Patient Illness: The Simcare Patient Model*, in *Computer Science* 2012, University of Minnesota: Minneapolis.
17. Gabrielsson, J., W. Jusko, and L. Alari, *Modeling of Dose-Response-Time Data: Four Examples of Estimating the Turnover Parameters and Generating Kinetic Functions from Response Profiles*. Biopharmaceutics & Drug Disposition, 2000. **21**: p. 41-52.
18. American Diabetes Association, *Standards of Medical Care in Diabetes—2012*. Diabetes Care, 2012. **35**(Supplement 1): p. S11-S63.