Using EMR Transactional Data for Personalized Clinical Decision Support

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INTRODUCTION

Collective intelligence techniques, used to predict stock prices and enhance consumer purchasing experience[1], remain unused in clinical medicine. With the advent of electronic medical records, digital patient data has grown exponentially and constitutes an untapped field where similar techniques could be applied[4]. If collectively farmed and intelligently filtered, the *de facto* collective clinical experience could be used to augment traditional guidelines to arrive at personalized clinical decision support[2]. The pharmacological treatment of hypertension was chosen as the clinical domain in which to explore the feasibility of this approach.

MATERIALS AND METHODS

Twelve-thousand-three-hundred-forty-seven hypertensive patients were seen at the Internal Medical Associates (IMA) clinic at Massachusetts General Hospital (MGH) between July 2004 and September 2009. Their relevant clinical and demographic variables[3], drug regimens and blood pressure measurements were collected from the clinic's electronic medical record system. Software employing a similarity algorithm was used to recommend successful drug regimens for an index patient based on successful treatments used by other well-controlled hypertensive patients.

RESULTS

Blood pressure control status and drug regimen effectiveness among similar patients were generated from the collective for an index patient (Figures 1 & 2).

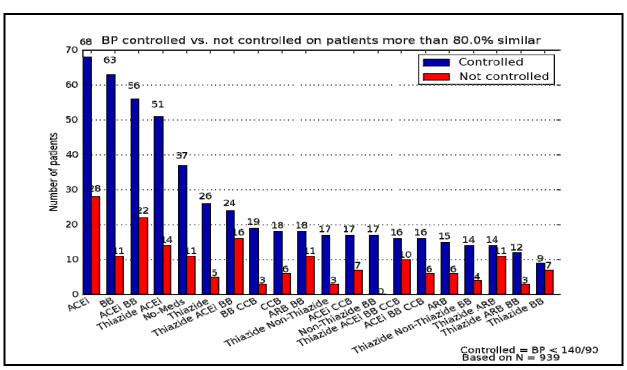

Figure 1. Top: Recommended drug regimens for an index patient.

As proof of concept, the system correctly predicted the actual blood pressure regimen for eight of ten randomly selected patients (Table 1). The system also provides the clinical rationale behind recommended therapies enhancing user trust. A collective experience decision support system (CEDSS) was successfully created as proof of concept. Such techniques are not only feasible but promising towards the goal of providing personalized, high quality, dependable care. Rigorous prospective studies to test point-of-care acceptance and real world effectiveness of these techniques are necessary.

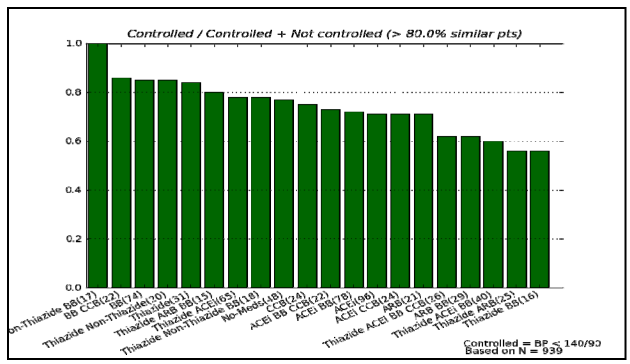

Figure 2. Effectiveness ratios for recommended regimens.

Patient ID	Number of similar patients (Min n = 100) (% similarity)	Actual regimen predicted within the first 5 regimens?	Prediction Place	Actual regimen
D	103 (90%)	No	8th	Thiazide,ACEi,BB
E	119 (75%)	Yes	3rd	BB,ACEi, Thiazide
F	311 (67%)	Yes	1st	ACEi
G	195 (91%)	Yes	4th	CCB,ACEi
H	148 (100%)	Yes	1st	ACEi,BB
I	142 (85%)	No	-	BB,CCB,ACEi
J	122 (70%)	Yes	2nd	Thiazide,ACEi
K	103 (90%)	Yes	3rd	BB
L	137 (90%)	Yes	5th	Thiazide,Non-Thiazide,ACEi
M	205 (80%)	Yes	1st	Thiazide

Table 1.Results from 10 randomly selected patients.

REFERENCES

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[3] Chobanian AV, et al. The Seventh Report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure: the JNC 7. JAMA 2003 May21; 289(19):2560-72.