The Effects of Time Pressure and Cost Transparency on Recommender Systems for Healthcare Cost Reduction[1]

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Abstract

Recommender systems have been successful at influencing behavior in a wide range of domains. In healthcare, clinical decision support and recommender systems are now increasingly being used to improve the quality of care. Such recommender systems have not yet been designed to reduce escalating costs, despite potential for doing so. This paper investigates recommender systems specifically designed to mitigate costs while maintaining outcomes. These systems would display multiple alternative procedures within the standard of care for each specific case, but along with their cost information at the point of care. Such real-time point-of-care recommendations however add to the time demands of the attending physician, who may have to spend more time reviewing the extra information presented. In this paper, we provide results from an experiment where medical practitioners used an EMR-like system enabled with recommendations to prescribe treatments. Time pressure and cost transparency were controlled. Key findings indicate a strong inclination among physicians to reduce healthcare costs when given the opportunity through cost transparency. However, our results show that time pressure plays an important and interesting role in the use of such recommendations. The results have significant implications for how intelligent recommender systems can reduce escalating healthcare costs as well as basic operations strategy in scheduling physicians.

Key words: Healthcare; Cost Transparency; Cost; Time Pressure; Clinical Recommender Systems; Agent-based simulation;

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1. Introduction

Healthcare costs have reached skyrocketing numbers in the US. With spending set at almost 18% of the GDP, headed for 20% by 2020 (Berwick and Hackbarth 2012), the US is the leading country in the world for healthcare spending. Particular to healthcare, prices for the same procedures vary tremendously depending on the paying party (Beck 2014; McGrory 2015). Insurance companies negotiate prices for each procedure based on the health plans provided (Thorpe 1997). These price variations are very significant. In an example reported by the Wall Street Journal (Beck 2014), the average charge for a joint-replacement surgery ranged from $5,300 in Ada, Oklahoma, to $223,000 in Monterey Park, California. Price variations have also been reported within a single city such as Jackson, Mississippi, where the cost of treating a case of heart failure varies from $9,000 in one hospital, to $51,000 in another (Beck 2014).

Providers though are typically unaware of healthcare costs. While physicians are able to identify generic drugs within each drug type they remain in the dark about exact diagnostics and treatments' costs (Beck 2014).

A strategy for reducing healthcare costs would therefore be to make cost information visible to medical providers at the right time. This could be accomplished through a medical recommender system that presents alternative prescription options that are: 1) appropriate for the patient being consulted, and 2) are lower in cost compared with the physician's initial selection.

Recommender systems have been used extensively is several applications to influence consumer decisions. In e-commerce, recommender systems have helped users find items meeting their exact specific needs driving up loyalty and allowing cross-selling of different items (Schafer, Konstan, and Riedl 1999).

There are numerous examples of apps and Web sites today that influence the movies users watch, the music they listen to, the articles they read or the auctions they participate in.

In healthcare, initial efforts have been made recently to integrate recommender systems with existing electronic medical records (EMRs) in order to optimize care plans (Duan, Street, and Xu 2011) and predict diagnoses (Hussein et al. 2012), suggesting the potential of such systems in this domain. However, the widely implemented clinical decision support systems (CDSS) are still more prevalent. Those differ from recommender systems in that 1) CDSS systems provide topic-related information to aid in decision making while recommender systems provide a set of alternatives to select from, and 2) recommender systems utilize users' selections and ratings to continuously refine the list of alternatives provided (Xiao and Benbasat 2007).

Mainly designed for alerting providers of abnormal events, clinical decision support systems (CDSS) have shown to improve provider performance outcomes -"*the rate of screening (such as retinal examination or urine protein measurement), medication use, and/or identification of at-risk behaviors"* (Garg AX et al. 2005), process health care measures -"*performing preventive services, ordering clinical studies, and prescribing therapies*" (Bright et al. 2012), and patient safety by reducing errors (Bates and Gawande 2003) and preventing adverse events (Duan, Street, and Xu 2011).

In this paper we investigate whether recommender systems can be used for the purpose of reducing rising healthcare costs, a significant global issue today that is particularly acute in the United States. Incorporating such recommendations in the medical decision making process can result in cost-aware providers, which could in turn help reduce costs. Even though several hurdles need to be crossed before price displays are integrated into health records (Riggs KR and DeCamp M 2014; Hoffer 2015), early research indicates promising outcomes for this initiative.

Having patients access intervention cost information has been associated with lower total claims amount (Whaley C et al. 2014). This can be explained using economic theory (Reinhardt, Uwe E. 2014). Experimental results also indicate a reduction, albeit at modest levels, in ordering laboratory test rates with the real-time display of cost information in electronic health records (Horn et al. 2013). Yet, the relationship between CDSS use and patient health outcome cost (Garg AX et al. 2005; Bright et al. 2012), workload and efficiency (Bright et al. 2012; Chaudhry et al. 2006) has yet to be consistently established.

Nonetheless, the use of such systems could suffer from lower acceptance rates because of the time pressure experienced by physicians during consultation. Physicians are increasingly asked to take on more cases to help manage both increasing demand as well as to manage costs. Over-booked providers may pay less attention to information deemed not essential to the specific patient case being considered. In fact because of the time involved in evaluating different recommendations (especially in emergency rooms), recommender systems have sometimes been either selectively used or completely removed (Drescher et al. 2011). Therefore, understanding the role of time pressure is important in the adoption of recommender systems in the healthcare domain.

In this paper we study the impact that price transparency and time pressure have in the use of recommender systems as well as in their ability to reduce healthcare costs. We do this from an experiment simulating a real EMR-like systems with realistic patient cases. Our subjects were forty actual medical practitioners who were randomized into one of four groups. Collectively they diagnosed and prescribed treatment options for 240 patient cases. Key findings indicate a strong inclination among physicians to reduce healthcare costs when given the opportunity through cost transparency. However, our results show that time pressure plays an important and interesting role in the use of such recommendations. The results have significant implications for how intelligent recommender systems can reduce escalating healthcare costs as well as basic operations strategy in scheduling physicians.

Controlled experiments, while powerful and often most highly valued, do limit the range of parameters that can be studied. Hence in addition we designed and built agent-based simulations to derive further insights on the mechanisms of how cost and time pressure influence outcomes and discuss those results as well. Such simulation models can provide more control and more parameters that might be experimented with and optimized in such stylized settings. The results provide several important insights on the ability to use medical recommender systems to address the increasingly complex challenge of battling rising healthcare costs.

A note of clarification before presenting more detail. Medical recommender systems could be useful for (a) *medical diagnosis*, given the symptoms, as well as (b) for suggesting *treatment options*, given diagnosis. While there are important questions in both scenarios, our scope is limited to scenario (b) - recommending appropriate procedures *given* a diagnosis. That is, we consider a case where providers use EMRs to make a diagnosis. Subsequently, in the same session, recommendations are used to provide information on possible treatments for this diagnosis.

2. Theoretical Background and Hypotheses

In this section we present the theoretical background and main hypotheses related to clinical recommender use under various cost and time pressure conditions.

2.1 The Cost Effect

Because of the lack of prior literature related to the impact of cost information on physician decision making, it is difficult to predict a physicians' propensity for low cost recommendations. In this domain, there is not direct link between the patient's cost of a prescribed procedure and a physician's utility. Prior literature lacks research that investigates the impact of cost in such scenarios.

However, all else being equal, we posit that it would be rational for physicians to select the less expensive alternatives for their patients. Recently, healthcare in the US has seen major reforms. More emphasis is being placed on enabling physicians to reduce healthcare costs. Today, medical providers are being held accountable for excessive healthcare costs. They are therefore more cost-sensitive. A survey of 2556 physicians indicated an incline towards "*limiting access to expensive treatments with little net benefit – 79%"*, and *"having decision support tools in their electronic records that show possible costs of tests and treatments - 70%".* (Emanuel EJ and Steinmetz A 2013).

Medical guidelines offer a wide range of alternatives when it comes to procedures to be prescribed. The optimal prescription goal depends on the ability to maintain a positive health outcome with minimal associated costs. Therefore, if alternative low-cost procedures being recommended are perceived to provide similar outcomes, they would most likely be used by physicians.

A potential risk with cost-sensitive recommender systems however, is bias resulting from the anchoring effect; an effect by which users' perceived recommendation value is highly influenced by previously seen ratings (Adomavicius et al. 2013; Cosley et al. 2003). In clinical cost-sensitive recommenders, providers could be biased by reference prices (Putler 1992) - current and past alternative procedure prices being displayed. Influence by a procedure recommendation might therefore vary based on lowest and highest (Rajendran and Tellis 2006), as well as the range (Janiszewski and Lichtenstein 1999) of alternative costs displayed.

The costs of the alternatives displayed might indicate the common prescription patterns among other physicians; which can in turn impact the influence by recommendations. Appeal to social norms has been shown to play a significant role in influencing human behavior in several settings such as environment conservation (Goldstein, Cialdini, and Griskevicius 2008). Based on that effect, systems have been designed to carefully select setting such as defaults (Johnson and Goldstein 2004), and recommendations' characteristics (Thaler, Sunstein, and Balz 2014). A display of cheaper alternative procedures for instance might indicate to the providers their divergence from the low-cost prescription norm and trigger more influence.

The appeal to social norm effect might be moderated by factors such as law (Posner 1997) and individual self-interest (Ostrom 2014; Olson 1965). However, under the main assumption that all recommended procedures are of similar clinical outcome, prescribing the lower-cost alternative procedure would not cause any liability issues. In fact, given the recent government's emphasis on reducing healthcare costs, altering prescription to the low-cost treatment option would be rather aligned with the physicians' self-interest.

We therefore consider two different recommender settings. In the first setting, referred to as the low-cost setting, physicians are presented with a list of low cost alternatives. In the other recommender setting, the list of recommendations presented includes a mix of high and low cost alternatives. This last setting we refer to as the mixed-costs recommender. We posit that while physicians would likely to be interested in viewing recommendations and adjusting to the lower treatment options (given that the resulting outcome is similar), it is anticipated that their behavioral change would also be affected by the cost of the recommendations presented. Hence, we make the following hypothesis:

H1. Adopting recommender treatment options is different (higher or lower) in the mixed-costs recommender settings than in the low-costs recommender setting.

2.2 The Time Pressure Effect

Recommendation time has been shown to be particularly important since providers are more likely to be influenced, and make medication prescription changes at the time of the prescription rather than adjustments later (Awdishu et al. 2015).

However, patient-physician encounter time has always been a scarce resource especially in managed care settings (Dugdale, Epstein, and Pantilat 1999; Linzer et al. 2000). During visits, physicians need to gather patient health information, complete administrative tasks, prescribe adequate treatments, and now, potentially review and react to system-generated alerts and recommendations.

Alerts seem to increase the amount needed for providers to prescribe treatments (Coleman et al. 2015); which in turn may increase physicians' time pressure. Among providers using extensive clinical information systems (EMR), time pressure during physical examination was correlated with negative physician outcomes (stress, burnout, lack of satisfaction, and intent to leave) (Babbott et al. 2014).

Under high time pressure, prior literature indicates that the load of information processed while making decisions is different than when under low time pressure. In 1992, Hahn and colleagues reported that when subjects in their study were not "hurried" while making decisions, their decision quality steadily increased as more information was presented (Hahn, Lawson, and Lee 1992). As applied to the medical domain, when enough consultation time is provided, physicians would benefit from processing more information.

Under low time pressure, physicians are therefore anticipated to view and process additional information provided by the recommender system. They would also be more inclined to "optimize" their treatment options to the best possible outcome/cost combination when time permits. On the other hand physicians under high time pressure, they would be inclined to process less information (Wright 1974), and thereby ignore systems recommendations. Therefore, we posit the following hypotheses:

H2-a.Viewing of recommendations is lower when physicians are under high time pressure than when under low time pressure.

H2-b. Adopting recommender treatment options is lower when physicians are under high time pressure than when under low time pressure.

Table 1 bellow lists the hypotheses developed in the "Cost and Time Pressure Effects Model".

Hypothesis	***Description***
H1	*Adjusting of treatment options is lower in the mixed-costs recommender settings than in the low-costs recommender setting.*
H2	*a. Viewing of recommendations is lower when physicians are under high time pressure than when under low time pressure.*
	b. *Adjusting of treatment options is lower when physicians are under high time pressure than when under low time pressure.*

Table 1: List of Hypotheses

3. Subjects and Methods

3.1 Subjects

A total of 40 medical providers participated in the experiment. By virtue of the generic nature of the cases used (related to primary care practice), clinicians of all specialties were able to complete them. Our pool of participants was mainly composed of medical doctors in Florida, most of whom having a considerable number of years of experience (Figure 1).

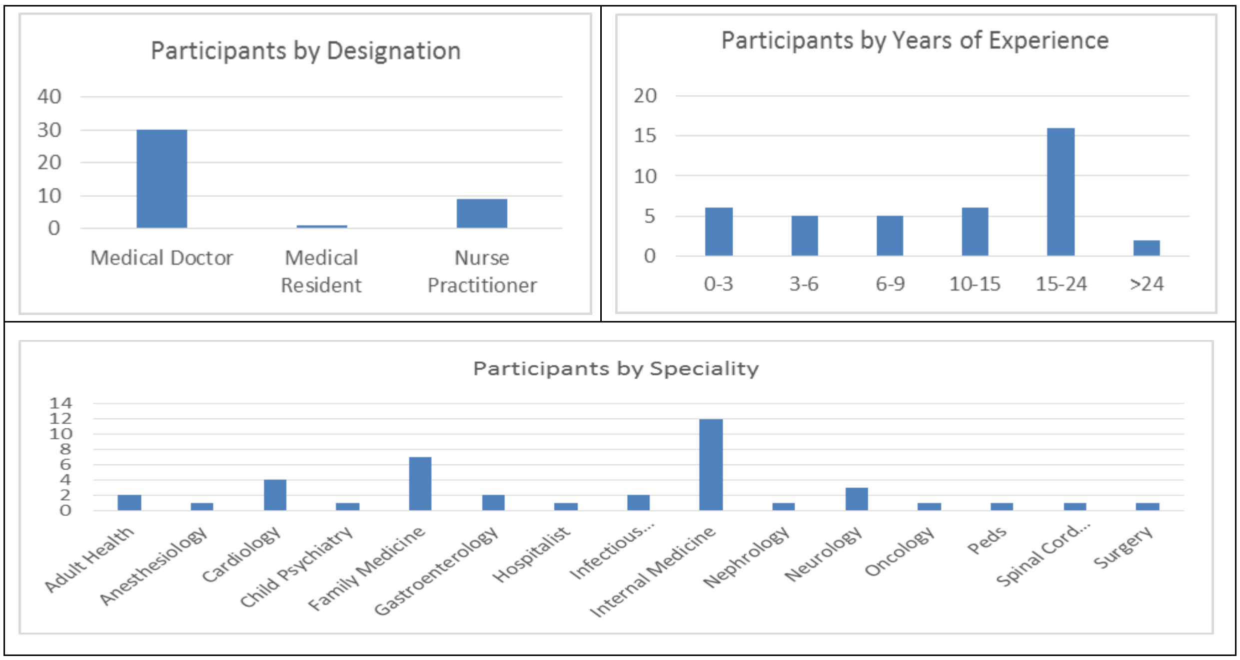

Figure 1: Participants Profiles

We were able to collect a balanced set of responses in terms of both subjects and cases. Ten complete responses were recorded in each of the four groups. With each participant completing three cases under low time pressure, and three cases under high time pressure, we had a set of 240 observations at the case level.

3.2 Experimental Design

An experiment was designed to evaluate our cost and time pressure effects model. We specifically looked at the effects of recommendation cost variance and time pressure on the physicians' probability of viewing and being influenced by medical recommendations.

The medical provider was presented a set of realistic medical cases, a description of the accompanying context, and a list of drugs to select from (for prescription purposes). After the medical provider made an initial selection of drugs to be prescribed, related cost information was displayed. The procedure cost presented provided the expected cost to the patient.

The medical provider then had the option to view systems recommendations. System recommendations included drugs similar to the one initially selected by the provider along with cost information.

Note that all recommendations presented were reviewed by two medical experts (Appendix A includes the list of medical cases created for the experiment). Providers were randomly placed into different grouped. Depending on their group assignment, providers were presented with either 1) all less expensive, or 2) mixed costs recommendations. Ranges of drug costs used in the experiment were estimated by clinical providers. However, costs of each specific drug were dynamically manipulated during the experiment. For the low-costs groups, recommendation costs were set to be lower than the cost of the procedure initially selected by the participant. For the mixed-costs groups, the initial treatment option (s) selected by the participant was dynamically set to a cost X. At least two recommendations were then presented with costs Y and Z; where Y<X<Z. The provider then had the option to alter his/her initial selection.

The experiment was conducted online using Qualtrics, which allowed for dynamic allocation of procedures and recommendations costs. Each provider's choice to 1) view the system recommendations, and 2) adjust the treatment option was recorded.

In order to simulate high time pressure, in half of the cases, we displayed a message indicating increased workload for the remaining time ("THE SYSTEM HAS JUST ADDED SEVERAL CASES TO YOUR QUEUE! Please try to complete all cases within the allocated time."), along with a timer counting the number of seconds spent on each page.

A counterbalanced design was used to control for the order effect. The order in which the time pressure treatment was presented varied in sequence. Follow-up survey questions were also presented to capture the providers' designation, specialty, and years of experience.

Three different treatments were identified for this experiment: Time Pressure, Recommendations Costs, and Time Pressure Display Order. Subjects in the experiment were presented six different fictional patient cases – validated from a focus group of independent medical experts prior to the study - and asked to select the most appropriate prescription regimen. A complete list of the medical cases uses for the experiment is available in Appendix A. A walkthrough of sample scenario is presented next.

First, providers were presented with an informed consent agreement page describing the purpose of the study, the study procedures, alternatives to participation, compensation and contact information. Participants' identity remained anonymous. However, participants had to enter the name of person referring them to the study; who in turn was responsible for verifying the participants' credentials before providing access to the experiment. Participants also had to certify that they were medical doctors, nurse practitioners, or medical residents.

In order to prevent learning effects, participants were also required to certify completing the experiment once only. Next, each provider was presented with the six fictional patient cases.

A patient's case (Figure 2 and 3) included the patient's general information, insurance information, demographics, active problem list, medication list (within and outside the current practice), any clinical alerts, chief complaint(s), history of present illness, past medical history, family medical history, social history, and a detailed visit description in Subjective, Objective, Assessment, and Plan (SOAP) format. The plan section was intentionally left out since the participating provider's task was to determine the treatment plan.

Patient 1

Name: James Smith DOB: 02/25/1972 Age: 42 Sex: Male

Visit Date: 2/11/2016 Visit Type: Problem Visit Visit Provider: YOU Primary Plan: BCBS

Problem List	Status
Duodenal Ulcer	Active

Medication List	Dose
Prescribed within Practice	
Ranitidine	150mg/12h
Maalox	200-200- 20mg/5mL
Prescribed outside Practice	

Clinical Alerts

New Endoscopic Exam Needed

Vital Signs

Date	BP	HR	RR	T(F)	Wt	Ht	O2
12/20/2014	124/78	82'	17	98.5	146lbs 3oz	5'6"	99%
04/07/2010	125/78	84	15	98.8	145lbs 6oz	5'6"	99%

Chief Complaint

- Epigastric Pain
- Weight Loss

History of Present Illness

James Smith is a 42 year old Caucasian male who presents today for recurrent epigastric pain treated in the last year with ranitidine. Patient experience loss of weight. He lost 5 pounds within the last month. Exacerbation of pain after meals. Patient has had endoscopic exam with biopsy that revealed the presence of 1 cm bulbar ulcer in the posterior part of the duodenum.

Figure 2: Sample Case (Part 1)

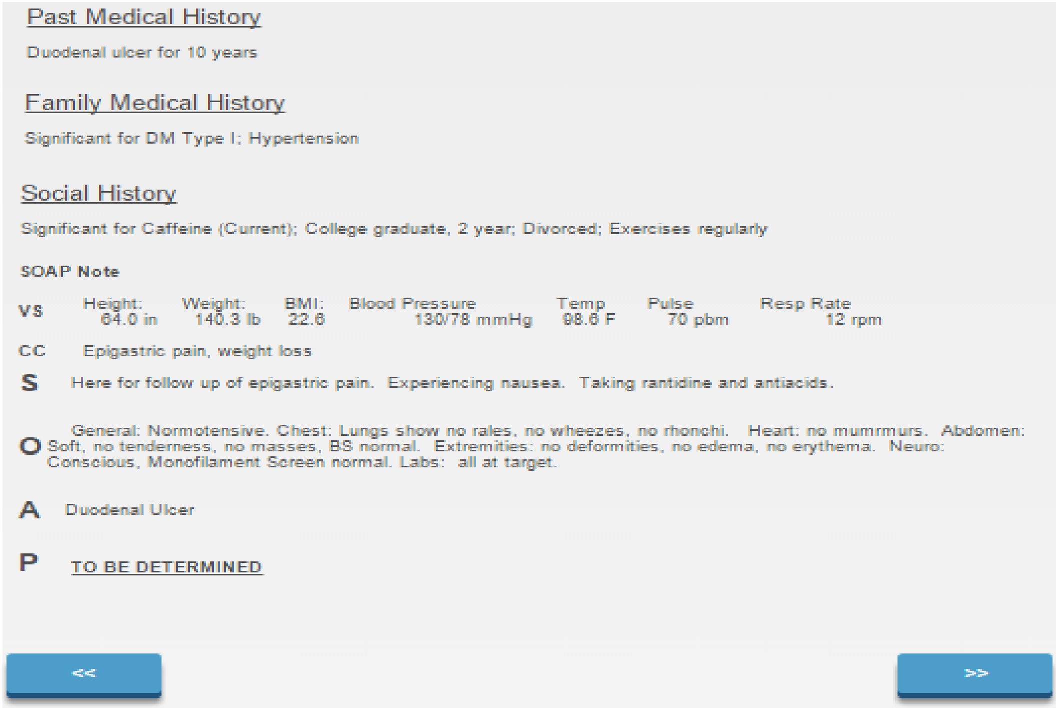

Figure 3: Sample Case (Part 2)

A list of treatment options for that specific patient case was then presented.

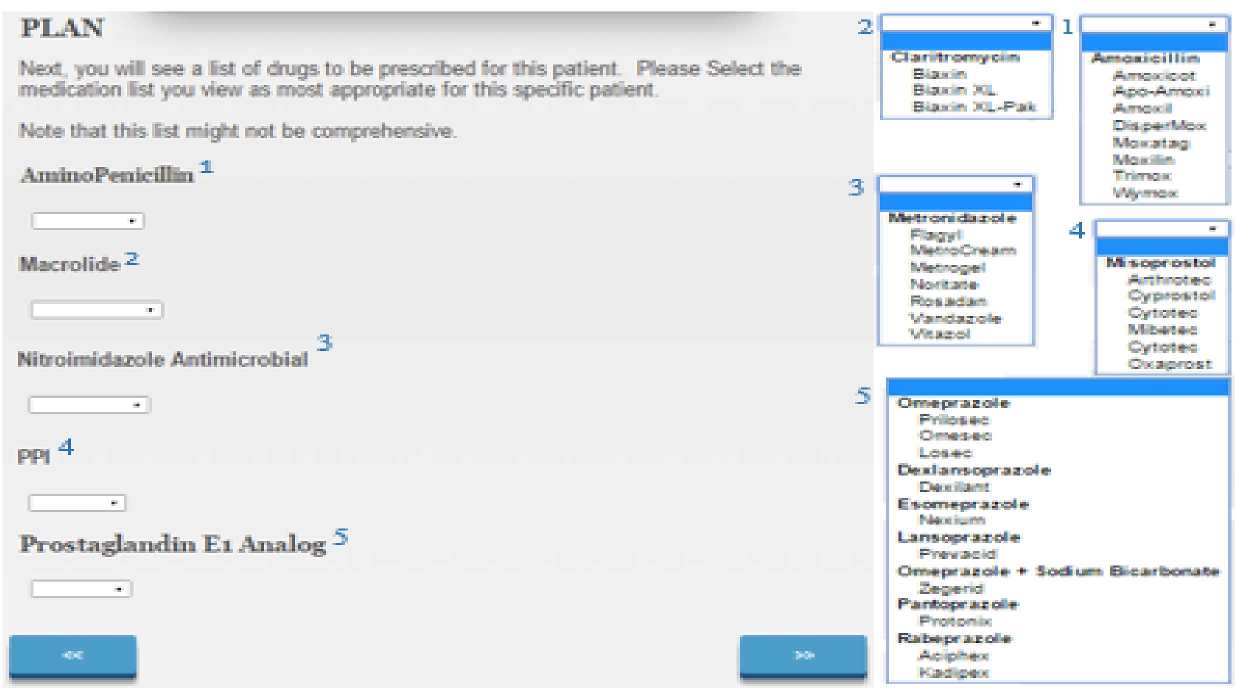

Figure 4: Prescription Options

A summary of the selected treatment plan was displayed, along with associated costs. Participants were then given the option to view system recommendations.

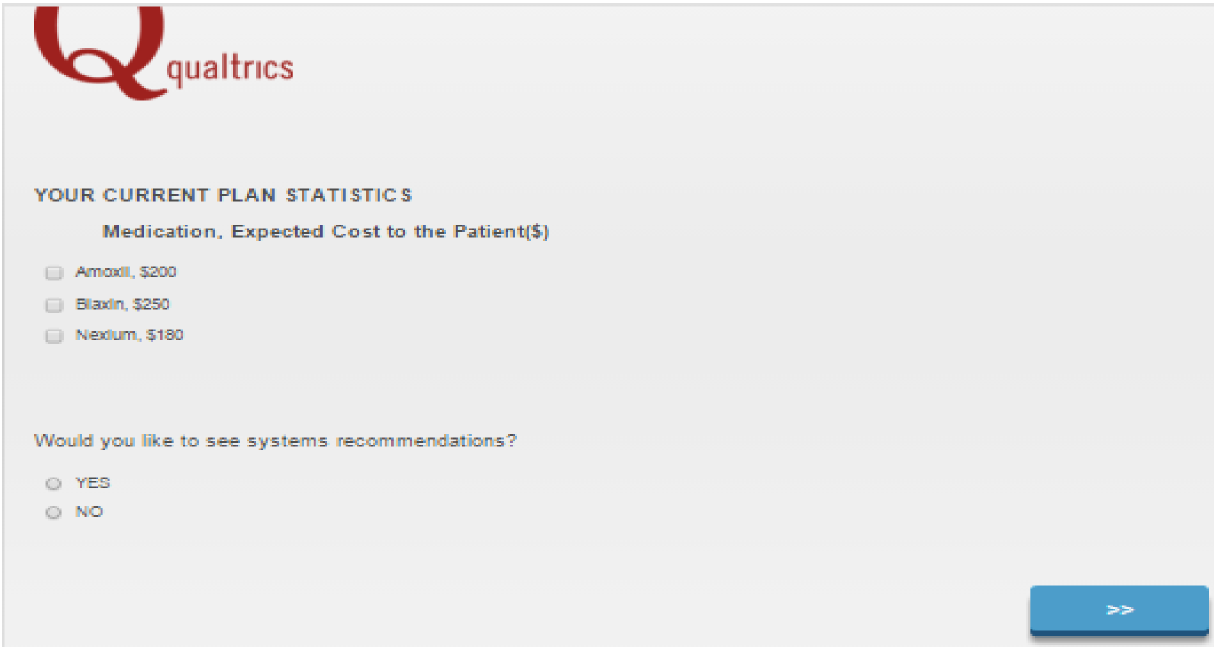

Figure 5: Treatment Plan with Cost Data

Based on the treatment categories selected, similar-outcome alternatives were presented along with cost information. Alternatives were either all of lower costs, or of mixed costs depending on the participants group.

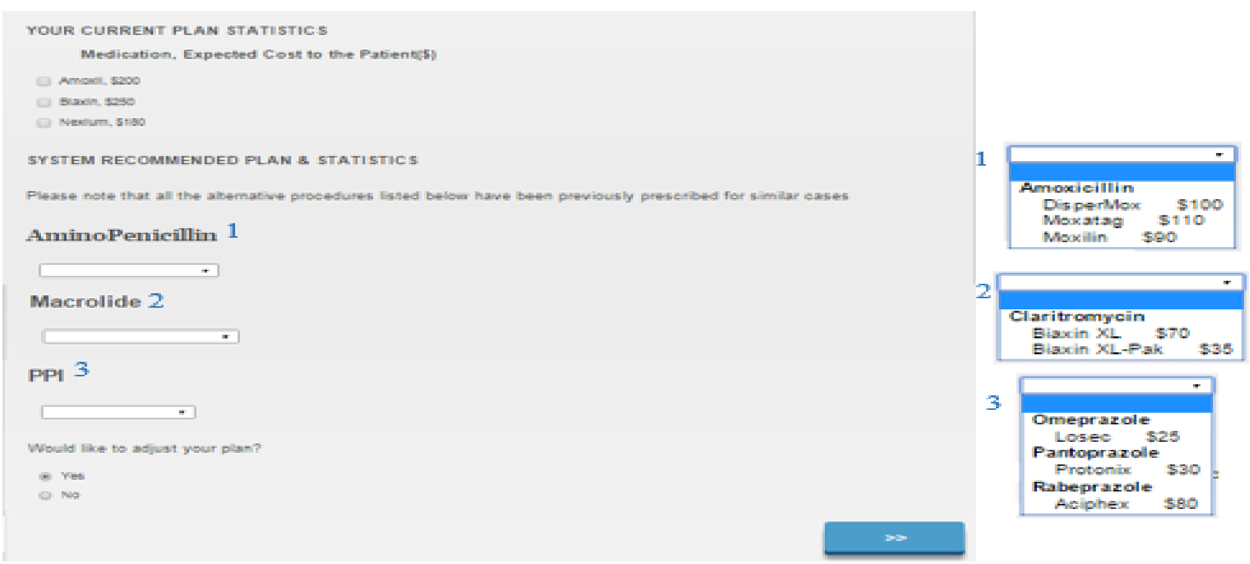

Figure 6: Alternative Treatment Options with Cost Data

Providers were then given the opportunity to confirm adjustment of treatment options or ignore the selected changes. If changes were confirmed, than an adjustment reason was required before proceeding further.

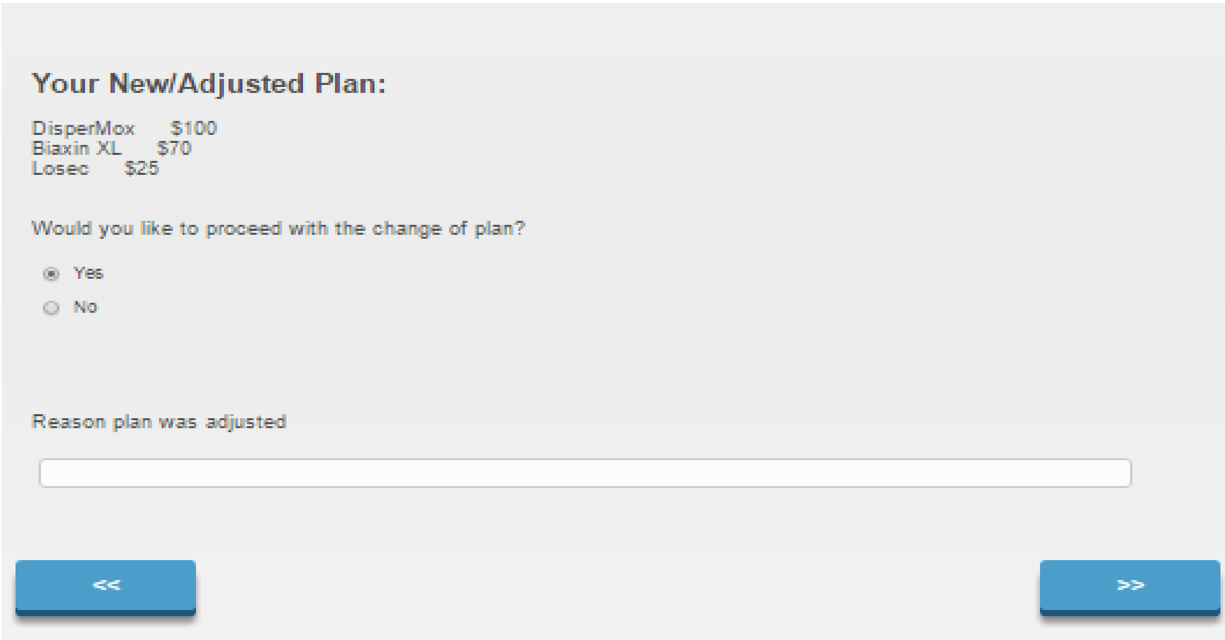

Figure 7: Adjustment Confirmation Screen

Depending on the treatment group, time pressure was simulated for the first or last 3 cases using a time restriction message on the top and side of the screen (Figure 8) and a timer counting the amount of time spent at every step of the prescription process.

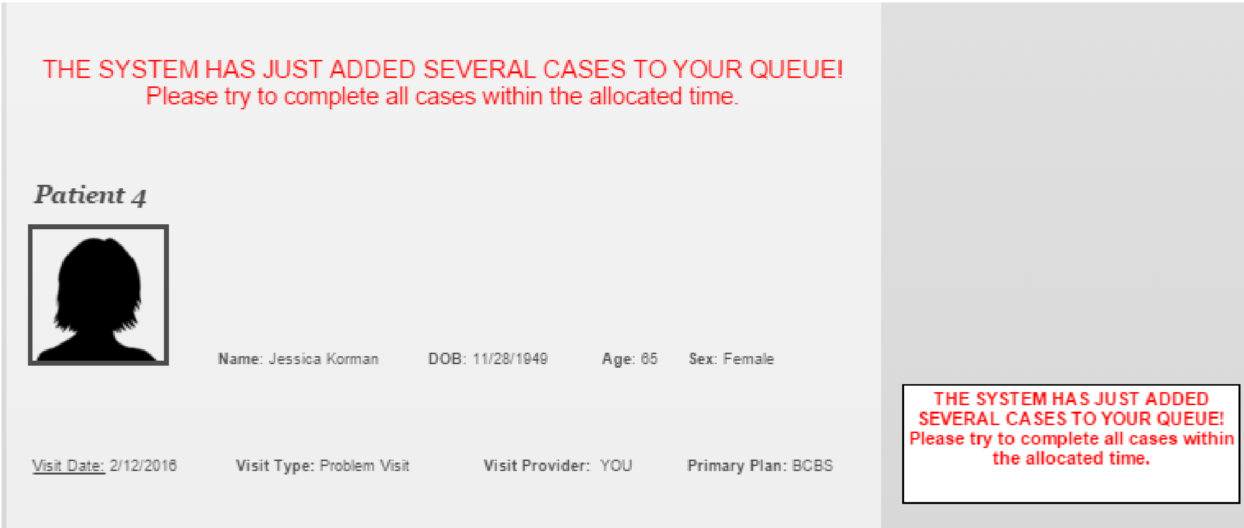

Figure 8: Time Pressure Simulation

A within-subjects design was used to evaluate the impact of time pressure on the physicians' use of the system recommendations. In half of the cases, the participants were under high time pressure (Table 2).

	Treatment 1 **Time Pressure**	
	Yes	**No**
Participant	3 Cases	3 Cases

Note: Each subject within the groups was presented Cases 1 – 6

Table 2: Experiment Treatment 1- Time Constraint Level

A between-subjects design was used to investigate the effect of the time pressure display order on the use of the recommendations. Depending on the group of the participant, the high-time pressure was either presented first (with cases 1-3) or last (cases 4-6)

A between-subjects design was also used to test the effect of cost on the use of the recommendations. Depending on their group, participants were presented with varying recommendation costs. Half of participants were presented a list of all low cost recommendations, while the other groups received recommendations of mixed costs. Participants were randomly placed into four different groups (Table 3).

		Treatment 2 Time Constraint Display Order	
		High TP First	*High TP Last*
Treatment 3 Recommendations Costs	*All Less Expensive*	Group 1	Group 2
	Mixed Costs	Group 3	Group 4

Note: Participants were randomly placed in each of the treatment groups.

Table 3: Experiment Treatments/Groups - Subjects

It is important to note that the cases used in the experiment were created in collaboration with two medical providers. Even though the cases are different in nature, they h were assessed by our experts as being similar in terms of complexity and risk levels.

4. Experiment Results & Statistical Findings

Traditional statistical methods were used to test the relative difference between the groups. Results provided insights on how the systems recommendations were used in different scenarios.

4.1 Data Description

Two different dependent variables were measured; namely: 1) "View" which represents the number of occurrences, the participants viewed the system recommendations, and 2) "Adjust" which refers to the number of times the participants adjusted their initial treatment plan to the recommended one.

The tables below provide descriptive statistics showing viewing and adjusting counts by cost group (Table 4) and time pressure level (Table 5).

Overall, we observed that participants viewed system recommendations for 181 out of the 240 cases, and adjusted their treatment plans for 117 out of the 240 cases. These large numbers indicate that the providers' had a general inclination to reduce patient treatment costs.

Recommendations Costs Variance Effect

When comparing the number of recommendations adopted in the low-cost recommendations groups, we see a significant difference indicating that participants did react differently to the recommendation cost treatment. In the low-cost recommendations groups, the number of adjustments reached 73 out of 120, when it only got to 44 out 120 in the mixed-costs recommendations groups.

Time Pressure Effect

Numbers in Table 4 below suggest that participants tended to view recommendations (95 versus 86), and adjust treatment options (59 versus 58) more frequently when under low time pressure.

		Time Pressure		
		High TP	***Low TP***	***Total***
Recommendations Costs	***All Less Expensive***	45, 35	53, 38	98, 73
	Mixed Costs	41, 23	42, 21	83, 44
	Total	86, 58	95, 59	181, 117

Table 4: Descriptive Statistics – Time Pressure Level (View Count, Adjust Count)

Time Pressure Display Order Effect

Table 5 below shows some differences in viewing and adjusting counts between the "high time pressure first" and "high time pressure last". With 98/120 versus 83/120 viewed recommendations, and 63/120 versus 54/120 adjusted treatment plans, the order in which time pressure is presented seemed to have an effect of our participants' propensity to change.

		Time Pressure Display Order		
		High TP First	***High TP Last***	***Total***
Recommendations Costs	***All Less Expensive***	53,39	45, 34	98, 73
	Mixed Costs	45, 24	38, 20	83, 44
	Total	98, 63	83, 54	181, 117

Table 5: Descriptive Statistics - Group Level (View Count, Adjust Count)

This could be explained by the fact that when time pressure is experienced early on, it could be perceived as the norm; and might therefore be overlooked. When, on the other hand, providers started off with ample time to consult patients, and then subject to time constraint, they were more likely to react by ignoring systems recommendations. The time pressure effect is hence posited to differ depending on the sequence of events.

4.2 Interaction Effect

Interestingly, looking at the interaction effects of all of our three different treatments, recommendation costs, time pressure level, and time pressure display order (Table 8), we see large differences of viewing and adjusting counts in some distinct cases. When high time pressure was presented last, we see that both viewing and adjusting counts varied depending on the time pressure level. In that scenario, viewing recommendations increased from 18/30 under the high time pressure to 27/30 under low time pressure for the low cost recommendations. That same number increased from 14/30 under the high time pressure to 24/30 under low time pressure for the mixed cost recommendations. Similarly, adjusting treatment options counts increased from 13/30 under the high time pressure to 21/30 under low time pressure for the low cost recommendations.

That same number increased from 9/30 under the high time pressure to 11/30 under low time pressure for the mixed cost recommendations.

		Time Pressure Display Order			
		High TP First		*High TP Last*	
		High TP	*Low TP*	*High TP*	*Low TP*
Recommendations Costs	*All Less Expensive*	27, 22	26, 17	18, 13	27, 21
	Mixed Costs	27, 14	18, 10	14, 9	24, 11

Table 6: Descriptive Statistics – Group/Time Pressure (View Count, Adjust Count)

This could be explained by the fact that, when a time constraint was imposed early on, it could be perceived as the norm and therefore did not trigger any time pressure. When, on the other hand, the time constraint was imposed after a phase of ample processing time, providers probably felt more significant time pressure. Therefore, the time pressure level effect was more substantial when time constraint was imposed later in the process.

Overall, the experiment provided very interesting insights on how physicians would react to cost-sensitive recommendations. The experiment also indicated that recommendation costs as well as time pressure did play a significant role in viewing systems recommendations, as well as in adjusting treatment prescriptions. To our knowledge, these are the first field results demonstrating the role of cost transparency and time pressure in the use of recommender systems to reduce healthcare costs.

While time pressure and cost settings have been shown to influence provider prescription patterns in our experimental settings, additional contextual factors could also impact the use of such recommender systems. These could be how physicians viewed cost (as a measure of quality for instance), or their abilities to withstand influence.

While these are inherently more difficult to control in experiments, the next section examines the use of an agent-based simulation for understanding how any of these factors could come into play to affect costs in the real world.

4.3 Statistical Findings

To investigate the statistical significance of our findings, we used a two-level logistic regression analysis. The analysis was performed at the patient case level (a total of 240 observations). Since each participant responded to six different cases (repeated measures as per out experiment's within-subject design), we used generalized estimating equations. Observations related to the same participants were therefore grouped within the same cluster; resulting in 40 different clusters.

Two different models were created for each of the dependent variables: Viewing system recommendations (View=1) and adjusting treatment options (Adjust=1).

$$Adjust = \beta_0 + \beta_1\ Recs + \beta_2\ TPLevel + \beta_3\ HiTPLast + \beta_4\ TPLevel*HiTPLast \quad (13)$$

$$View = \beta_0 + \beta_1\ TPLevel + \beta_2\ HiTPLast + \beta_3\ TPLevel*HiTPLast \quad (14)$$

Where *Recs*, *TPLevel*, and *HiTPLast* are all dichotomous predictors. Recs was set to 0 for low cost recommendations, and 1 for mixed cost recommendations. *TPLevel* was set to 0 for low time pressure and 1 for high time pressure. *HiTPLast* was set to 0 when time pressure was presented for the first cases and 1 for cases when time pressure was presented last.

Statistical results for our adjusting treatment options model (Table 6) indicate the significance of all of our model terms. Since reference coding was used for this analysis, the results shown represent the comparison of each level of the independent variable with the reference level.

The recommendations cost term was significant at (p=0.0198) indicating a significant difference in adjusting treatment options between the cases showing low cost recommendations versus cases with mixed costs recommendations; providing support for our hypothesis H1-b. The time pressure term was significant with a p value of 0.0470. We also see a significant effect of time pressure display order (p=0.0269). Last, as expected, the interaction between time pressure level and order to time pressure display was highly significant with a p value of 0.0031.

Table 7: Analysis of GEE Parameter Estimates for "Adjust =1"

Empirical Standard Error Estimates

Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr>|Z|
Intercept		-1.1234	0.5279	-2.1580	-0.0888	-2.13	0.0333
Recs	0	1.0331	0.4435	0.1638	1.9024	2.33	0.0198
TPLevel	0	0.7245	0.3647	0.0097	1.4393	1.99	0.0470
HiTPLast	0	1.0347	0.4676	0.1182	1.9512	2.21	0.0269
TPLevel* HiTPLast	0 0	-1.3719	0.4638	-2.2810	-0.4629	-2.96	0.0031

When it came to viewing system recommendations, all terms in the model were significant other than recommendation costs (Table 7). Hence, providing support for hypothesis H1.

Table 8: Analysis of GEE Parameter Estimates for "View =1"

Empirical Standard Error Estimates

Parameter		Estimate	Standard Error	95% Confidence Limits		Z	Pr>|Z|
Intercept		0.1335	0.3950	-0.6407	0.9078	0.34	0.7353
TPLevel	0	1.6011	0.5294	0.5634	2.6387	3.02	0.0025
HiTPLast	0	2.0637	0.6072	0.8736	3.2537	3.40	0.0007
TPLevel* HiTPLast	0 0	-2.7867	0.7469	-4.2506	-1.3228	-3.73	0.0002

5. Influence Dynamics - Comprehensive Model

Understanding of the underlying influence dynamics, which models the use (or lack thereof) of the recommender under different conditions is essential to the design.

In this section, we further describe how time pressure and cost variance occur in clinical settings based on our experimental results. We also present additional factors assumed to influence recommendation use. We then present an influence dynamics model using the stated factors.

The five factors used in the influence model are based on the presence of time pressure, risk, procedure cost, provider type, decision quality and the predisposition to be influenced. Appendix B includes detailed definitions for each of the factors.

Influence Dynamics - Comprehensive Model

In this section, we extend our influence dynamics model to include factors other than cost and time pressure. In collaboration with a few physicians in the practice we learned that several influence dynamics would be anticipated to exist in the provider network. Under different levels of risk and time pressure, physicians are anticipated to view different amounts of information, and therefore accept recommendations at different rates. We present one such comprehensive model.

5.1.1 High Time Pressure / High Risk

This scenario represents the case of emergency department physicians. In this case, physicians ignore such systems in order to save time (Drescher et al. 2011). In this scenario, users will consider an alternative prescription for review only if the outcome of the recommended procedure significantly exceeds the outcome of the pre-selected procedure.

Because of lack of time, physicians will most likely go with their chosen procedure and refrain from considering alternatives even if they are cost effective.

5.1.2 Low Time Pressure / High Risk

Under normal time pressure, physicians will be more disposed to evaluating a large number of alternatives, especially when the protocol is not well defined or when a new drug is introduced.

A typical example of this scenario would be oncology, where the medical community has not yet reached consensus regarding treatment options. In this case, if the recommender system is trusted, providers will most likely consider procedures that have been shown to 1) yield better patient outcomes, and 2) represent the best cost alternative. It is important to note that physicians are expected to select the procedure that best fits their cost-related type.

5.1.3 Low Time Pressure / Low Risk

Under low time pressure, physicians are most likely to consider alternative options. Typically, primary care providers (PCP) would fall in this category. Those are physicians who usually work outside hospital settings, and are also more conscious about healthcare costs. Additionally, the PCP's office work setting allows for less time pressure, and therefore more opportunity to evaluate various recommendations. That is, even if the recommender system is not fully trusted, physicians can allocate the time to evaluate alternative procedures that are potentially beneficial.

Figure 9 presents the influence dynamics under the different scenarios of varying physicians' levels of time pressure, as well as procedure costs, outcomes, risks, influence predisposition. The individual paths in the tree are self-explanatory and map to the dynamics discussed in this section.

```
TP – High
|   Risk – Low ➔ <Ignore – Use Current>
|   Risk – High
|   |   Influence Predisposition – Low ➔ <Ignore – Use Current>
|   |   Influence Predisposition – High
|   |   |   Decision Quality – Low ➔ <Ignore – Use Current>
|   |   |   Decision Quality – High ➔ < Prob Swap>
TP – Low
|   Risk – High
```

| | Influence Predisposition – Low ➔ <Ignore – Use Current>
| | Influence Predisposition – High
| | | Decision Quality – Low ➔ <Ignore – Use Current>
| | | Decision Quality – High
| | | | Cost Relative Difference – Positive & Provider Type – Price-praising ➔ < Prob Swap>
| | | | Cost Relative Difference – Negative & Provider Type – Price-sensitive ➔ < Prob Swap>
| Risk – Low
| | Decision Quality – Low ➔ <Ignore – Use Current>
| | Decision Quality – High
| | | Cost Relative Difference – Negative ➔ < Prob Swap>

Figure 9: Influence Dynamics – Comprehensive Model

6. Comprehensive Model Evaluation: Agent-Based Simulation

To evaluate the comprehensive influence dynamics model presented above, we implemented a recommender system that we refer to as Top-N++. Top-N++ is a Top-N recommender which provides procedure cost and outcome information at the time of prescription. That information is expected to alter the provider's prescribing behavior; thereby allowing such systems to steer the prescription behavior towards better patient outcomes and lower healthcare costs.

The recommender keeps track of a list of alternative procedures pertaining to each diagnosis, along with the outcome, the cost, and the rate of prescription associated with each procedure.

6.1 Simulation Model

We consider a group of 100 providers. Each provider has a list of patients to be consulted daily. Providers vary in terms of their individual attributes:

- Attitude towards the recommender system (high versus low trust).

- "Time Pressure Retardancy α", "Delay-Pressure Factor β", and "Time Pressure Capacity".
- Attitude towards cost difference (PQ, or PS). The price-indifferent provider type was not included in the model since it is not anticipated to affect overall cost savings.

Patients' appointments are set at fixed intervals of time. However, delay is introduced stochastically during the simulation lifetime. Three sources of delay are included. The real patients' arrival time includes a random delay, modeling the late arrival of some patients. If the delay exceeds a specific threshold, the appointment is cancelled, or re-scheduled for a later date. The consultation time includes a random delay, as some consultations might exceed the expected allocated time. With a small probability, X minutes are added the provider's daily delay to model any unexpected emergency cases.

Using a traditional top-N algorithm, the recommender displays the three popular most prescribed procedures. Hoverer, the Top-N++ also presents information about the cost, the patient outcome, and the percentage of prescription associated with each procedure.

The provider first pre-selects a procedure, and then evaluates the list of procedures presented by the recommender using the influence dynamics described earlier.

In order to evaluate the performance of the TOP-N ++recommender under time pressure, we consider the overall cost savings metric. Cost savings is defined as the difference in cost between the pre-selected procedure and the recommended one. In case the provider is not influenced by the recommender system, the cost savings is considered to be null. Note however, that the system recommends procedure based on percentage of prior prescription by other providers, and not on costs.

Therefore, depending on the provider type, the cost of the recommended procedure could be higher than the pre-selected one; in which case, the cost savings amount will be negative.

$$\mathrm{M} = \sum(\mathrm{Cost}_{\mathrm{PreSelected}} - \mathrm{Cost}_{\mathrm{Recommended}})$$

6.2 Simulation Results

Using an agent-based simulation we analyzed the TOP-N++ recommender's performance under various levels of time pressure. The analysis considers different scenarios based on the providers' types, risk, outcome and cost variance. Below we present interesting results under a few cases and discuss the interpretation.

Figure 10 shows the aggregate costs savings generated by provider prescriptions as a function of the experienced delay. Results indicated decreasing trend as the experienced delay increased; simulating higher levels of time pressure. Because of the stochastic nature of the recommendation adoption simulation (probabilistic swap – Figure 9), the cost saving function was not strict monotonic.

Figure 10A compared the costs savings generated by providers of different cost types while treating high risk patients. When patient delays are low, providers are under low time pressure and tend to select recommended procedures that are aligned with their cost type. Therefore, when a large percentage of providers are price-sensitive, low cost recommendations are selected and positive cost savings are generated. Under the same settings, a group of mostly price-praising providers generates negative cost saving. As delay builds up and time pressure increases, providers do not take the time to evaluate cost effective alternatives. However, it is interesting to see how the initial selections made by physicians under low time pressure impacted the subsequent selections.

Because initially selected (cost effective) procedures gained higher prescriptions rates, they were included in the Top-N++ recommendations list used in subsequent iterations. Thus, under high time pressure, the group of price-sensitive providers continued to generate positive cost savings, while price-praising providers generated negative cost savings for most levels of time pressure. When time pressure reached a high level, more providers ignored system recommendations (Figure 9); causing the cost-savings amounts to be independent of provider type.

Figure 10B shows that treatments with high cost variance only generated significant cost savings under low time pressure. This is because providers need time to evaluate lower cost treatment options and determine how suitable they might be for each specific patient. Such cases include considering generic versus brand name prescription drugs.

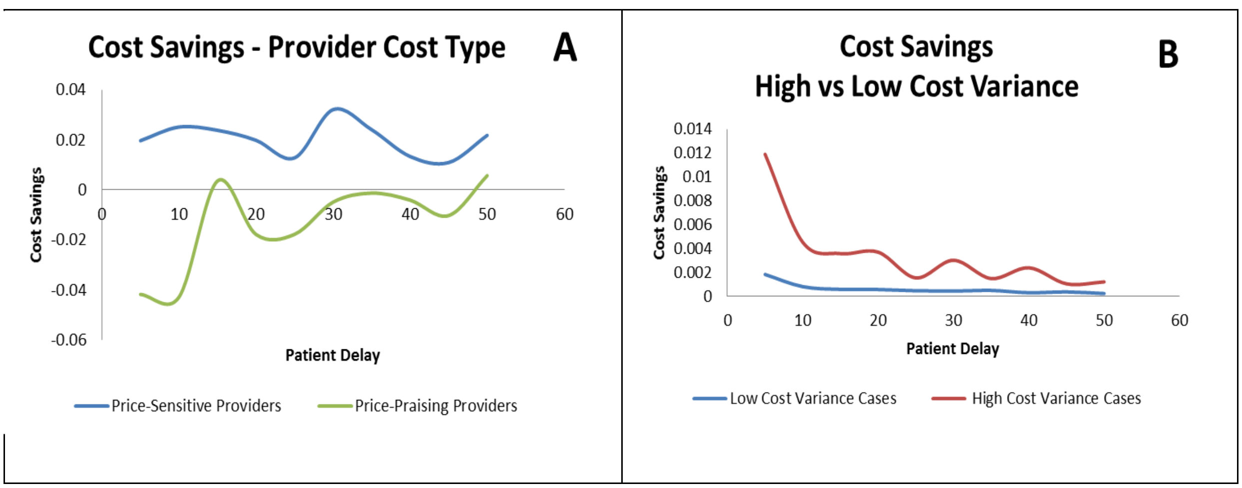

Figure 10: Sample Simulation Results – Top-N++

7. Conclusions

This study explored the use of recommender systems in clinical practice in order to reduce elevated healthcare costs. Our strategy for lowering healthcare costs leverages medical recommender systems by presenting procedure cost information at the time prescription. To our knowledge, this is the first study to make use recommender systems for the purpose of cost reduction in healthcare.

Results from our experiment completed by physicians revealed some very interesting insights on how medical practitioners would be influenced by such systems. Key findings indicate a general inclination among physicians to reduce patients' share of cost. However, this influence effect was shown to be moderated by recommendations attributes such as cost variance and time pressure. When recommendations presented are all less expensive than the procedure initially selected, the influence rates were significantly high. Evidence also shows that consultation of both, viewing of and influence by recommendations, were significantly lower under high time pressure.

Other factors impacting the use of recommendations in the medical settings also include outcome, risk, and influence predisposition. The influence dynamics of such factors were identified with collaboration with domain experts. In settings of high time pressure and high risk, cost-sensitive recommendations were anticipated to be ignored. Under low time pressure, recommendations were more likely to be evaluated; and eventually used. The influence by recommendations was also anticipated to be higher for physicians with higher influence predisposition such as novice providers.

The evaluation of our cost-sensitive recommender was performed using an agent-based simulation under various scenarios of risk, outcome, and influence predisposition. Results indicated generally positive cost savings from using the recommender system; confirming our experiment results. Savings were also less substantial in high time pressure cases where recommendations tended to be ignored. Cost savings were also minimal when the majority of providers were price-praising; associating high cost procedures with higher outcome.

8. Contributions and Future Work

This study provides an initial understanding on physicians' use of cost information presented through recommender systems. We show how simple recommender systems that incorporate procedure cost can result in significant cost savings and better outcomes in healthcare. In experimental research, the study provides a contribution on designing experiments with time pressure treatments. Our findings clearly indicate that applying high time pressure towards the end of the experiment triggers a high sense of time pressure; as opposed to providing a higher workload and time constraint upfront. A plausible explanation being that when high loads are presented first, they are perceived to be the norm, and hence do not produce time pressure.

Recently, there have been several initiatives to reduce healthcare costs in the US indicating both the importance and urgency of the matter. Our findings suggest that presenting similar-outcome low-cost alternatives to physicians at the time of prescription would be well adopted by physicians in the practice; leading to an overall reduction of healthcare costs.

Our simulation results indicate that such systems might not be equally effective in different healthcare sectors. In environments of high risk and high time pressure settings, for example, these low-cost recommendations would most likely be ignored. Such systems might also create additional burden for physicians whenever time is scarce. The practical implications are that, when implementing cost-sensitive recommender systems, it is important to identify, and take into account, the characteristics of the specific setting in which the system will be used.

There are important design implications as well. Clinical decision support systems have been suffering from very low adoption rates (Drescher et al. 2011), especially in less severe cases (Awdishu et al. 2015). The lack of providers' influence by CDSS recommendation has been attributed the to alert fatigue (Kesselheim et al. 2011), and alert inappropriateness (McCoy et al. 2012). It has also been observed that resident physicians were more likely to override alerts (Awdishu et al. 2015), but took longer to dismiss interruptive alerts compared to other providers (McDaniel et al. 2015).

Design of effective recommender systems in healthcare requires a deep understanding of the application domain context. Incorporating contextual information – *such as time, place, and user company* (Adomavicius and Tuzhilin 2015) into the design of recommender systems has been proven to improve performance.

Simply incorporating price information in medical records, as previously experimented, gives physicians the binary option of either prescribing the procedure or not. A more elaborate alternative would be to develop a cost-sensitive recommender system which displays multiple alternative procedures, along with cost information. Such systems need to be specifically designed to maintain health outcomes, and mitigate costs.

In order to bypass the time pressure effect associated with providers' low adoption rate in less severe cases, recommender systems can potentially be used to influence patients. Since its first inception in the early 1990s, the patient's personal health record (PHR) scope of functionalities has shifted from simple access to patient information, to interacting with medical records, to empowering the patient to improve his/her own health outcomes (Bouayad, Padmanabbhan, and Ialynytchev 2016).

Integrated with the new patient health record, content-based recommender system can use patients' comprehensive medical record to help provide patients with more personalized care (Wiesner and Pfeifer 2010). Collaborative-based recommender systems can also be integrated with patient health social platform to generate recommendations for specific groups of patients sharing the same medical conditions (Song et al. 2011).

With the recent shift towards promoting patient engagement and shared/collaborative patient-provider decision making, recommendations sent to the patient can indirectly influence the providers' prescription patterns; and in turn impact health outcomes and costs (Arterburn et al. 2012).

There are interesting possibilities for further research. While this study indicates the potential success of our novel strategy in practice, additional research is needed to generalize and advance our knowledge.

Even though our experiment was completed by physicians, and therefore provided a relatively high level of reliability, our sample size was small. More research is needed to duplicate the study and generalize our findings. Because a convenient sample was used, the majority of participants were specialized in internal medicine. Additionally, the medical cases used in the experiment were pertaining to primary care; limiting generalizability. Future research is needed to assess the physicians influence by such cost-sensitive recommendations in different specialties where cost variance among similar-outcome alternatives might be more or less relevant, and where time pressure might be more significant.

Last, our cohort of subject consisted mostly of highly experienced physicians; which might have biased our results. Medical residents and less experienced doctors might react differently to recommendations provided by the system. If recommendations provided by the system are deemed reliable, novice providers might be more inclined to use the system recommendations; which would be viewed as the general practice. These providers would also include a younger generation, relatively more acquainted with the use of recommender systems in general.

In the recommender systems research, more studies are needed to assess the effect of time pressure on recommendation adoption. Because of the increasing prevalence of recommender systems in different settings, such as online retail, a better understanding of factors impacting their use is crucial. Such understanding would enable the design of more effective recommender systems; leading to higher returns. Personalized recommenders, for example, could be designed to learn and take into account time pressure in order to display person-tailored as well as context-tailored recommendations.

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Appendix A: Experiment Instrument

Patient 1

Name: James Smith **DOB**: 02/25/1972 **Age**: 42 **Sex**: Male

Visit Date: **SYS DATE** **Visit Type:** Problem Visit **Visit Provider:** YOU **Primary Plan:** BCBS

Problem List	**Status**
Duodenal Ulcer	Active

Medication List	**Dose**
Prescribed within Practice	
Ranitidine	150mg/12h
Maalox	200-200- 20mg/5mL

Allergy List
Latex Exam Gloves
Sulfur (rash)

Clinical Alerts
New Endoscopic Exam Needed

Vital Signs

Date	**BP**	**HR**	**RR**	**T(F)**	**Wt**	**Ht**	**O2**
12/20/2014	124/78	82	17	98.5	146lbs 3oz	5'6"	99%
04/07/2010	125/78	84	15	98.8	145lbs 6oz	5'6"	99%

Chief Complaint

- Epigastric Pain
- Weight Loss

History of Present Illness

James Smith is a 42 year old Caucasian male who presents today for recurrent epigastric pain treated in the last year with ranitidine. Patient experience loss of weight. He lost 5 pounds within the last month. Exacerbation of pain after meals. Patient has had endoscopic exam with biopsy that revealed the presence of 1 cm bulbar ulcer in the posterior part of the duodenum.

Past Medical History

Duodenal ulcer for 10 years

Family Medical History

Significant for Hypertension

Social History

Significant for Caffeine (Current); College graduate, 2 year; Divorced;

SOAP Note

	Height:	Weight:	BMI:	Blood Pressure	Temp	Pulse	Resp Rate
VS	64.0 in	140.3 lb	34.7	130/78 mmHg	98.6 F	70 pbm	12 rpm

CC Epigastric Pain, weight loss

S Here for follow up of epigastric pain. Experiencing nausea. Taking rantidine and antiacids.

O General: Normotensive. Chest: Lungs show no rales, no wheezes, no rhonchi. Heart: no mumrmurs. Abdomen: Soft, no tenderness, no masses, BS normal. Extremities: no deformities, no edema, no erythema. Neuro: Conscious, Monofilament Screen normal. Labs: all at target.

A Duodenal Ulcer

P **TO BE DETERMINED**

PLAN
Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

AminoPenicillin
- ❍ Amoxicot
- ❍ Apo-Amoxi
- ❍ Amoxil
- ❍ DisperMox
- ❍ Moxatag
- ❍ Moxilin
- ❍ Trimox
- ❍ Wymox

Macrolide
- ❍ Biaxin
- ❍ Biaxin XL
- ❍ Biaxin XL-Pak

Nitroimidazole Antimicrobial
- ❍ Flagyl
- ❍ MetroCream
- ❍ Metrogel
- ❍ Noritate
- ❍ Rosadan
- ❍ Vandazole
- ❍ Vitazol

PPI
- ❍ Prilosec
- ❍ Omesec
- ❍ Losec
- ❍ Dexilant
- ❍ Nexium
- ❍ Prevacid
- ❍ Zegerid
- ❍ Protonix
- ❍ Aciphex
- ❍ Kadipex

Prostaglandin E1 Analog
- ❍ Arthrotec
- ❍ Cyprostol
- ❍ Cytotec
- ❍ Mibetec
- ❍ Oxaprost

Patient 2

Name: Shawn Jones **DOB: 02/25/1960** **Age: 55** **Sex: Male**
Visit Date: **SYS DATE** **Visit Type:** Problem Visit **Visit**
Provider: YOU **Primary Plan:** BCBS

Problem List	**Status**
Diabetes Mellitus, Type II	Active
Hypertension	Active

Medication List	**Dose**
Prescribed within Practice	
Metformin	2 500mg
Captopril	2 25mg

Allergy List
None

Clinical Alerts
Diabetics: Eye Exam Needed
Diabetic: Foot Exam

Vital Signs

Date	**BP**	**HR**	**RR**	**T(F)**	**Wt**	**Ht**	**O2**
06/20/2014	135/80	82`	17	98.5	246lbs 3oz	5'8"	99%
12/07/2013	130/79	84	15	98.8	240lbs 6oz	5'8"	99%

Chief Complaint

- Diabetes follow-up

History of Present Illness

Shawn Jones a 55 year old Caucasian male who comes in for a follow-up visit. In the previous encounter, patient's dose of metformin was increased to 500mg, 3 times a day. Patient presented today with an A1C level of 9% and glucose test of 220. Patient not following recommended diet and physical activity.

Past Medical History

Diabetes Type II
Hypertension

Family Medical History

Social History

Significant for Alcohol (Current); College graduate, 4 year; Married;

SOAP Note

VS	Height: 68.0 in; Weight: 250.0 lb; BMI: 34.7; Blood Pressure 140/85 mmHg; Temp 98.6 F; Pulse 70 pbm; Resp Rate 12 rpm
CC	follow up diabetes, BP
S	Here for follow up of diabetes, and hypertension. Taking medications without difficulty. Not following DM diet. Self-checked blood glucose unstable. Increased urination. Excessive thirst. Fatigue. Dizziness.
O	General: Normotensive, in no acute distress. Chest: Lungs show no rales, no wheezes, no rhonchi. Heart: no mumrmurs, no rubs, no gallops. Abdomen: Soft, globular, no tenderness, no masses, BS normal. Extremities: no deformities, no edema, no erythema. Neuro: physiological, no peripheripathy. Monofilament Screen normal. Labs: Glucose 220, A1C 9%.
A	Hypertension, Diabetes II
P	**TO BE DETERMINED**

PLAN
Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

Biguanides
- ❍ Fortamet
- ❍ Glucophage
- ❍ Glucophage XR
- ❍ Glumetza
- ❍ Riomet

Sulfonylureasfonylureas

- DiaBeta
- Glycron
- Glynase
- Micronase
- Glipizide XL
- Glucotrol
- Glucotrol XL
- Amaryl

Meglitinides

- Glufast
- Starlix
- Prandin

Thiazolidinediones

- Actos
- Avandia
- Rezulin

DPP-4 inhibitors

- Tradjenta
- Onglyza
- Januvia

GLP-1 receptor agonists

- Tanzeum
- Byetta
- Victoza
- Lyxumia

SGLT2 inhibitors

- Invokana
- Farxiga
- Suglat

Alpha-Glucosidase Inhibitors

- Precose
- Glyset
- Voglib

Bile Acid Sequestrants

- Questran
- Welchol
- Colestid
- Colestipid

Combination Pills

- ❍ Metaglip
- ❍ Glucovance
- ❍ Duetact
- ❍ Actoplus Met
- ❍ Prandimet
- ❍ kombiglyze
- ❍ Janumet

Insulin therapy

- ❍ Novolog
- ❍ Levemir
- ❍ Lantus
- ❍ Apidra
- ❍ Humulin N
- ❍ Novolin N
- ❍ Humalog

Patient 3

Name: Claudia Santiago **DOB**: 04/25/1995 **Age**: 19 **Sex**: Female
Visit Date: SYSTEM DATE **Visit Type:** Problem Visit **Visit Provider:** YOU **Primary Plan:** Aetna

Problem List	**Status**
Asthma	Active

Medication List	**Dose**
Prescribed within Practice	
Loratidine	1- 10mg
Fluticasone	2- 50mcg
Prescribed outside Practice	
Albuterol	As needed

Allergy List
Aspirin
Non-steroid anti-inflammatory drugs

Clinical Alerts

Vital Signs

Date	**BP**	**HR**	**RR**	**T(F)**	**Wt**	**Ht**	**O2**
11/04/20014	124/84	78	15	98.8	158lbs 3oz	5'6"	99%
07/07/20013	124/79	83	15	98.8	147lbs 7oz	5'6"	99%

Chief Complaint
- Dyspnea
- Wheezing

History of Present Illness
19 year old female comes in for worsening of asthma symptoms. She refers to difficulty breathing with effort. Constant dry cough. The condition is worse at night. Wheezing.

Past Medical History

Chronic sinusitis; Allergic Rhinitis; Usual Childhood disease

Family Medical History

Social History

Non-smoker; High-school graduate; Exercises regularly

SOAP Note

VS	Height:		Weight:		BMI:	Blood Pressure		Temp		Pulse		Resp Rate	
	66.0	in	150.0	lb	28.7	121/68	mmHg	98.6	F	70	pbm	28	rpm
CC	Asthma												
S	Here for worsening of asthma symptoms. Shortness of breath. Wheezing. Taking medications without difficulty.												
O	General: Normotensive, tachypneic. No fever. Chest: Lungs show wheezes, rhonchi. Heart: no mumrmurs, no rubs, no gallops. Abdomen: Soft, no tenderness, no masses, BS normal. Extremities:no deformities, no edema, no erythema. Neuro: physiological, no peripheripathy. Monofilament Screen normal. Labs: all at target.												
A	Asthma												
P	**TO BE DETERMINED**												

PLAN

Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

Adrenergic Bronchodilators

- ❍ AccuNeb
- ❍ Airet
- ❍ Proventil
- ❍ Proventil HFA
- ❍ Ventolin
- ❍ Ventolin HFA
- ❍ Volmax
- ❍ Vospire ER
- ❍ Adrenalin
- ❍ Adrenalin Chloride
- ❍ Asthmahaler
- ❍ Auvi-Q
- ❍ EpiPen
- ❍ Primatene Mist
- ❍ Twinject
- ❍ Isuprel
- ❍ Isuprel Mistometer
- ❍ Medihaler-Iso
- ❍ Xopenex
- ❍ Xopenex Concentrate
- ❍ Xopenex HFA
- ❍ Alupent
- ❍ Orciprenaline
- ❍ Metaprel
- ❍ Brethine
- ❍ Bricanyl
- ❍ Brethine

Anticholinergics Bronchodilators

- ❍ Tudorza Pressair
- ❍ Atrovent
- ❍ Atrovent HFA
- ❍ Spiriva
- ❍ Spiriva Respimat

Methylxanthines

- ❍ Dilor
- ❍ Dylix
- ❍ Lufyllin
- ❍ Theo-24
- ❍ Theo-Dur
- ❍ Uniphyl

Leukotriene Modifiers
- ❍ Singulair
- ❍ Accolate
- ❍ Zyflo

Inhaled Corti Costeroids
- ❍ Aerospan
- ❍ Qvar
- ❍ Pulmicort
- ❍ Asmanex
- ❍ Flovent

Bronchodilator Combinations
- ❍ Combivent
- ❍ Symbicort
- ❍ Advair Diskus
- ❍ Advair HFA
- ❍ Anoro Ellipta

Oral Corti Costeroids
- ❍ Baycadron
- ❍ Cortef
- ❍ Orapred

Patient 4

Name: Jessica Korman **DOB**: 11/28/1949 **Age**: 65 **Sex**: Female
Visit Date: **SYSTEM DATE** **Visit Type:** Problem Visit **Visit**
Provider: YOU **Primary Plan:** United Health

Problem List	**Status**
Chronic Ischemic Heart Disease	Active

Medication List **Dose**

Prescribed within Practice

Prescribed outside Practice

Aspirin	1 – 50 mg
Nitroglycerin	3 – 1 mg

Allergy List

Clinical Alerts

Vital Signs

Date	**BP**	**HR**	**RR**	**T(F)**	**Wt**	**Ht**	**O2**
04/20/2013	130/78	82`	17	98.5	190lbs 3oz	5'6"	99%
07/07/2012	135/79	83	15	98.8	186lbs 7oz	5'6"	99%

Chief Complaint
- Nocturnal Cough
- Fatigue

History of Present Illness

65 year old African-American female, diagnosed with chronic ischemic heart disease in 2013, refers dyspnea during her ordinary activities and asthenia. Symptoms began 3 months ago, and worsened in the past 2 weeks.

Past Medical History

Chronic Ischemic Heart Disease

<u>Family Medical History</u>
Mother died with stroke at the age of 60

<u>Social History</u>

College graduate, 4 year; Married

SOAP Note

VS	Height:		Weight:		BMI:	Blood Pressure		Temp		Pulse		Resp Rate	
	64.0	in	202.0	lb	32.6	130/78	mmHg	98.6	F	70	pbm	12	rpm
CC	Dyspnea, nocturnal cough, fatigue												
S	Here for worsening cardiac failure symptoms. Pt suffers from dyspnea, asthenia.												
O	General: Pt normotensive, tachypneic. Lung auscultation show inspiratory rales, wheezes. Cardiac Auscultation: gallop, no mummurs. Abdomen: normal, no hepatomegaly. Lower Extremities: slight maleolar edema. Labs: all at target.												
A	Chronic Ischemic Heart Disease												
P	**<u>TO BE DETERMINED</u>**												

PLAN
Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

Calcium Channel Blocking Agents
- ❍ Norvasc
- ❍ Cardizem
- ❍ Diltzac
- ❍ Tiazac
- ❍ Cardene IV
- ❍ Adalat CC
- ❍ Nifediac CC
- ❍ Procardia
- ❍ Calan
- ❍ Isoptin
- ❍ Verelan

Cardiac Glycoside
- ❍ Cardoxin
- ❍ Lanoxicaps
- ❍ Lanoxin

Vasodilators
- ❍ Nitro-Bid
- ❍ Nitrostat
- ❍ Rectiv

Angiotensin Converting Enzyme Inhibitors
- ❍ Capoten
- ❍ Monopril
- ❍ Aceon
- ❍ Enalapril

Peripheral Vasodilators
- ❍ Cyclospasmol
- ❍ Voxsuprine
- ❍ Pavaco
- ❍ Papacon
- ❍ Pavagen

Angiotensin Receptor Blockers
- ❍ Edarbi
- ❍ Teveten
- ❍ Candesartan
- ❍ Cozaar
- ❍ Benicar
- ❍ Micardis

Statins
- ❍ Lipitor
- ❍ Lescol
- ❍ Mevacor
- ❍ Livalo
- ❍ Pravachol
- ❍ Crestor
- ❍ Zocor

Platelet Aggregation Inhibitors
- ❍ Ecotrin
- ❍ Fasprin
- ❍ Miniprin
- ❍ Clavix
- ❍ Clopirad
- ❍ Plavix

Patient 5

Name: Natasha Wood **DOB**: 7/25/1991 **Age**: 23 **Sex**: Female
Visit Date: **SYSTEM DATE** **Visit Type:** Problem Visit **Visit**
Provider: YOU **Primary Plan:** United Health

Problem List Status

Hypothyroid Active

Medication List	**Dose**
Prescribed within Practice	
Synthroid	25 mcg daily
Fioricet	325 mg one tablet every 6 hours as needed for headache
Prescribed outside Practice	
Claritin	10 mg daily as needed

Allergy List
Macrodantin – emesis
NSAIDS/ ASA – GI Bleed
Food allergies: oranges – hives, Chocolate – anaphylaxis

Clinical Alerts
EKG
Echocardiography

Chief Complaint

- Fatigue

History of Present Illness

Pt. presents to the office for a routine checkup. She denies feelings of chest pain or pressure. She denies any edema or numbness in her extremities. She states she has felt chronic fatigue over the past three months.

Past Medical History
Hypothyroid x 2 yrs.
Family Medical History
Mother: HTN (alive)
Father: Stroke at age of 40

Maternal Grandmother: Ischemic heart disease (deceased)
Maternal grandfather: HTN (deceased)
Paternal grandmother: DM type II (deceased)
Paternal Grandfather: CAD, MI at age 52 (deceased)

Social History

Patient denies ever having used tobacco or alcohol. She lives alone and has never been married. She has no children. She drinks 3 cups of coffee every morning.

SOAP Note

VS	Height: 62.0 in; Weight: 111.0 Lb3.2oz; BMI: 20.34; Blood Pressure: 110/80 mmHg; Temp: 98.5 F; Pulse: 70 pbm; Resp Rate: 18 rpm
CC	Fatigue
S	23 y.o. with familiar antecedents of familial hypercholesterolemia and stroke at early age (like 40 in father), presents in routine exam high levels of cholesterol and triglycerides.
O	**General:** African American female who appears her age, in no acute distress. Appears to have a flat affect. **Skin:** Light brown, warm and dry. No lesions, rashes or ulcers. Skin turgor good **Hair:** texture is course, shoulder length black hair. Equal distribution with no areas of hair loss **Chest:** Symmetric expansions, no rales/ rhonchi/ wheezes noted. Respirations equal and clear throughout all lung fields **Heart:** RRR, S1 and S2 audible, No gallops or rubs, PMI @ 5th ICS @ midclavicular line, no edema noted, peripheral pulses present **Abdomen:** Soft, non-tender, non-distended. Liver and spleen non palpable. **Ears:** TM pearly gray, bony landmarks visible, no bulging or drainage noted bilaterally. **Eyes:** PERRLA, no erythema or visible discharge noted bilaterally **Nose:** No erythema or edema noted. No nasal discharge. Septum intact. **Throat:** No visible exudates, no petechiae. Mucus membranes moist and pink. Teeth intact **Neck:** No lymphadenopathy noted. Thyroid non-palpable **Neuro:** CN II – XII intact, sensory intact, strength equal bilaterally, no tremors or nystagmus noted. **Labs: TC** – 310 **TG –** 200 **HDL –** 40 **LDL –** 240 **ALT/ AST –** 130
A	Hyperlipidemia
P	**TO BE DETERMINED**

PLAN

Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

Statins

- ❍ Lipitor
- ❍ Lescol
- ❍ Mevacor
- ❍ Livalo
- ❍ Pravachol
- ❍ Crestor
- ❍ Zocor

Combination Statins

- ❍ Caduet
- ❍ Advicor
- ❍ Vytorin

Bile Acid-Binding Resins

- ❍ Prevalite
- ❍ WelChol
- ❍ Colestid

Fibrates

- ❍ Abitrate
- ❍ Antara
- ❍ Tricor
- ❍ Triglide
- ❍ Lopid

Nicotinic Acid

- ❍ Niacor
- ❍ Niaspan
- ❍ Slo-Niacin

Selective Cholesterol Absorption Inhibitors

- ❍ Zetia

Patient 6

Name: Aliya White **DOB**: 9/25/1967 **Age**: 47 **Sex**: Female
Visit Date: **SYSTEM DATE** **Visit Type:** Follow-up Visit **Visit Provider:** YOU **Primary Plan:** United Health

Problem List	**Status**
Hypertension	Active

Medication List	**Dose**
Prescribed within Practice	
Motrin PRN headaches	600mg 3-4x weekly
Exforge	10/320 mg tablet once daily
Prescribed outside Practice	

Allergy List

Clinical Alerts

Vital Signs

Date	**BP**	**HR**	**RR**	**T(F)**	**Wt**	**Ht**	**O2**
02/05/2015	185/104	69`	18	98.5	170lbs 3oz	5'6"	99%

Chief Complaint
- Follow –up of physical exam – HTN
- Headaches

History of Present Illness
47 y.o. A.A. F presents to clinic for f/u of physical exam findings. Found to be hypertensive during physical exam 1 week ago. PCP ordered blood work.

<u>Past Medical History</u>
Hypertension x 20 yrs.

<u>Family Medical History</u>
Father has HTN, is on dialysis for renal failure. Mother has DM Type II.
<u>Social History</u>

Accountant, works 50-60 hrs/week, lives alone, poor diet: lots of fast food. Caffeine 2-3 /day, occasional EtOH, smokes 1 pack/day (27 pack-year hx). Would like to exercise more, but is often too tired.

SOAP Note

VS	Height:		Weight:		BMI:	Blood Pressure		Temp		Pulse		Resp Rate			
	65.0	in	168.0	lb	28.0	180/104	mmHg	98.6	F	62	pbm	12	rpm		
CC	F/u of physical exam														
S	47 y.o. A.A. F presents to clinic for f/u of physical exam findings. Found to be hypertensive during physical exam 1 week ago. PCP ordered blood work.														
O	BUN 35, SCr 1.8, 24-hr urine: >1 g /day proteinuria, glucose: 99mg/dL. Lipid panel: TC: 240mg/dL, TG: 1 70mg/dL, HDL: 34mg/dL LDL:144 mg/dL														
A	- Pt has uncontrolled HTN - Smoking, caffeine, stress and poor diet increase BP and risk of CV disease. Lifestyle modifications and smoking cessation will help to reduce BP.														
P	<u>**TO BE DETERMINED**</u>														

PLAN
Next, you will see a list of drugs to be prescribed for this patient. Please select the medication list you view as most appropriate for this specific patient. Note that this list might not be comprehensive.

Calcium Channel Blocking Agents
- ❍ Norvasc
- ❍ Cardizem
- ❍ Diltzac
- ❍ Tiazac
- ❍ Cardene IV
- ❍ Adalat CC
- ❍ Nifediac CC
- ❍ Procardia
- ❍ Calan
- ❍ Isoptin
- ❍ Verelan

Cardiac Glycoside
- ❍ Cardoxin
- ❍ Lanoxicaps
- ❍ Lanoxin

Vasodilators
- ❍ Nitro-Bid
- ❍ Nitrostat
- ❍ Rectiv

Angiotensin Converting Enzyme Inhibitors
- ❍ Capoten
- ❍ Monopril
- ❍ Aceon
- ❍ Enalapril

Peripheral Vasodilators
- ❍ Cyclospasmol
- ❍ Voxsuprine
- ❍ Pavaco
- ❍ Papacon
- ❍ Pavagen

Angiotensin Receptor Blockers
- ❍ Edarbi
- ❍ Teveten
- ❍ Candesartan
- ❍ Cozaar
- ❍ Benicar
- ❍ Micardis

Statins
- ❍ Lipitor
- ❍ Lescol
- ❍ Mevacor
- ❍ Livalo
- ❍ Pravachol
- ❍ Crestor
- ❍ Zocor

Platelet Aggregation Inhibitors
- ❍ Ecotrin
- ❍ Fasprin
- ❍ Miniprin
- ❍ Clavix
- ❍ Clopirad
- ❍ Plavix

Appendix B: Simulation Variable Definitions

<u>Time- Pressure:</u> Models time-pressure as a function of delay build-up.

- People react to delay build-up differently depending on various factors such as personality and experience.
- Providers are assumed to differ in the amount of build-up needed to occur before they start experiencing time pressure. We refer to that amount as time pressure retardancy α.
- Once the medical doctor exceeds his/her "time pressure retardancy" threshold, time pressure starts to increase gradually with a "delay-pressure coefficient" β. Because delay needs to accumulate before creating build-up and thus generating time pressure, the relationship between delay build-up and time pressure is not linear. We model the time pressure (TP) as a sigmoid function of delay build-up (x), as follows:

$$\mathrm{TP} = \frac{\mathbf{1}}{\mathbf{1}+ e^{(-x/\beta+\alpha)}} \text{ where } \alpha>0 \text{ and } \beta>0 \qquad (15)$$

<u>Risk</u>: Represents the severity of the patient case presented. Emergency department physicians for example deal with higher risk cases.Primary care providers usually handle more routine low risk cases. In addition, specialties where new diagnoses are set, or new drugs are prevalent could also be categorized as being of a relatively higher risk.

<u>Cost Relative Difference:</u> The relative cost difference between the procedure recommended by the system and the cost difference of the procedure initially selected by the providers.

<u>Provider Type</u>: Represents the different types of providers based on how they view cost.

- *The Price-Indifferent Provider (PI):* In the US medical system, because most procedures are covered by external payers, many doctors typically ignore cost (until recently, when the new healthcare law was enacted).

- *The Price-Quality Provider (PQ):* As with several consumers, some medical practitioners and patients may perceive price as a cue to quality (Tellis and Gaeth 1990). For the "Price-Quality Provider", a procedure might be viewed as more effective because it is more expensive.
- *The Price-Sensitive Provider (PS)*: By providing cost information some providers might be susceptible to altering their prescribing behavior in favor of the less expensive procedure. With the new regulations in place in the US, medical practitioners are indeed held accountable for any unnecessary costs imposed on the system.

Influence Predisposition: The likelihood of being influenced by the recommendation provided by the system. Low influence predisposition is expected to be exhibited by experienced physicians who do not necessarily recognize the need of using decision support systems or recommenders during consultation (Berner, 2008). High influence predisposition on the other hand would be typically observed among medical students and/or residents.

Decision Quality: Represents the health outcome associated with each specific prescribed treatment/diagnostic procedure. In this paper, aggregate levels of success of each procedure could be used as a measure of outcome (e.g. "63% of all patients who use drug X see a reduction in triglycerides"). We assume these are "given" for each procedure type.

Cost Variance: Represents the variance in cost between alternative procedures associated with the same medical case. All alternatives are assumed to generate similar health outcomes.