OptiHealth: A Recommender Framework for Pareto Optimal Health Insurance Plans

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Abstract: Choosing a health insurance plan, even when the plans are standardized, is a daunting task. Research has shown that the complexity of the task leads consumers to make non-optimal choices most of the time. While a number of systems were introduced to assist the selection of health insurance plans, they fail to significantly reduce the main causes of poor decisions. To address this problem, this paper proposes OptiHealth, a recommender framework for Pareto optimal selection of health insurance plans. The proposed framework is based on (1) actuarial analysis of medical data and a method to accurately estimate the expected annual cost tailored to specific individuals, (2) finding and presenting a small number of diversified Pareto optimal plans based on key performance indicators, and (3) allowing decision makers to iteratively conduct a trade-off analysis.

1 INTRODUCTION

A decision on choosing a health insurance plan should not be taken lightly. Such a decision has major implications for a person's health, finance and well-being. At an individual or family level, the financial implication is significant with some individuals spending a large share of their income on healthcare.

Choosing a plan is a complex task. Sometimes there are dozens or even hundreds of plans to choose from, each with a set of features. A large body of evidence shows that individuals select health plans poorly even when the number of plans is small. The main causes of poor decisions found in the literature (Hibbard *et al*, 1997), (Johnson *et al*, 1993), (McWilliams *et al*, 2011), (Tversky, Kahneman, 1974) are complexity, excessive number of choices, inability to estimate health outcomes, cognitive bias and high cognitive load. The result is that consumers end up using simplified heuristics and fail to make a Pareto optimal decision that is best suited to their needs.

To help consumers choose health plans, a number of Decision Support Systems have been developed and are publicly available. In section 3 we analyze six widely used systems which are representative of the state of the art for health plan selection. These systems are simplistic in nature; they basically provide a list of all available plans sorted by a particular plan feature such as deductible. Our conclusion is that none of them significantly reduces the main causes of non-optimal decision making.

To address this gap, we propose a recommender framework for Pareto optimal selection of health insurance plans called OptiHealth. Designed to overcome the main causes of human errors or biases, the framework comprises a detailed decision methodology and a recommender to guide a decision maker through the entire health plan selection process. It extracts demographic and health information from the user and employs an algorithm to match this information with actuarial medical data in order to predict the healthcare utilization for the upcoming year. It estimates the total annual expected cost for each plan and then recommends a small number of Pareto optimal plans. It allows decision makers to iteratively conduct a trade-off analysis, and presents alternatives that improve key performance indicators while minimizing the increase in the expected cost. The recommender guides decision makers to the preferred trade-off among Pareto optimal alternatives.

The contributions of this paper are as follows. First, we analyze the root causes of non-optimal decisions and identify desirable features of a technical solution. Second, we design a method to estimate the total annual cost of health plans based on actuarial patient data. Third, we develop recommender

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framework that addresses the desirable features and produces Pareto optimal recommendations best suited to decision makers' needs.

The paper is organized as follows: Section 2 is an overview of health insurance in the United States and the issues that surround health insurance decision-making. Section 3 proposes a set of desirable features in a Decision Support System and evaluates six widely used public systems. Section 4 shows the recommender framework through an example. Section 5 discusses the personalization of plan cost estimation. Section 6 describes the architecture of the recommender framework. Section 7 describes potential future research and concludes the paper. We use the terms "Framework" or "recommender framework" to describe our decision methodology and the term "recommender" to refer to the system at the core of the Framework.

2 OVERVIEW OF THE DECISION TO SELECT A HEALTH INSURANCE PLAN

In the United States, health care is delivered almost exclusively by private medical providers such as hospitals, doctors and pharmacies. Access to health care is facilitated by private insurance companies through health insurance plans. The menu of plans to choose from depends on a person's eligibility, employment status and what the employer offers. The set to choose from range from a handful of plans to hundreds of plans. As the number of choices increase, so does the difficulty of making a decision, which can cause cognitive overload.

A health insurance plan is a complex product. In general, a plan has a menu of benefits, limitations, charges a premium and imposes cost-sharing like deductibles, copays and coinsurance. A copay is a fixed dollar amount paid for a particular service while coinsurance is a percentage of the service cost that the insurer is responsible for. Deductible is an amount the beneficiary pays before coinsurance kicks in (copays are not subject to deductible). Insurance plans limit the risk of a catastrophic financial loss by instituting a ceiling that the insured is responsible for. This is called maximum out-of-pocket and does not include premiums.

Choosing a health insurance plan is a daunting task even when the plans are standardized in terms of coverage, as is the case of the plans in the U.S. exchanges of the Patient Protection and Affordable Care Act (ACA). The reason is two-fold: there are dozens of plan characteristics to take into consideration, plus it requires the estimation of future utilization of health services as well as the total annual cost for each plan. This difficulty is well established in the literature and was acknowledged by (Frakt, 2014).

A large body of evidence shows that individuals select non-optimal health plans even when the set of choices is small. (Quincy, 2012) conducted consumer testing studies and claimed that participants struggled to assess the overall coverage of a plan and had difficulty understanding cost-sharing concepts and what they meant in their particular case. (Abaluck *et al*, 2011) evaluated the choices of elders across their insurance options under the Medicare Part D Prescription Drug plan. They found that study participants placed much more weight on plan premiums than on expected out-of-pocket costs. Their partial equilibrium welfare analysis implied that welfare would have been 27 percent higher if patients had all chosen rationally, demonstrating not only that participants chose a plan poorly but also overweighed the premium factor. (Heiss, 2013) confirmed these findings; their study suggests that fewer than 25% of individuals enrol in plans that are ex-ante as good as the least costly plan specified by the (Medicare Plan Finder, 2016) tool made available to seniors by the Medicare Administration, and that consumers on average had expected excess spending of about $300 per year.

One might argue that the root cause of the above findings was cognitive decrease due to aging, but other studies found similar effects in younger populations. (Johnson, 2013) examined how well people make plan choices versus how well they think they do. They conducted six experiments asking subjects to choose the most cost-effective plan using websites modelled on health exchanges. Participants had to estimate the number of doctor visits and the out-of-pocket costs, and choose between a set of four or eight plans. The results matched earlier studies showing that unassisted, and without any tool, consumers made non-optimal health plan decisions. They selected the best option only 42% of time with four plans and 21% with eight. Also these non-optimal choices cost the 4-plan group $200 more per year.

The issues we identified with unassisted health plan decision making are: heavy cognitive load, cognitive bias, inability to estimate health outcomes and simplified heuristics.

Heavy Cognitive Load

A substantial body of work in cognitive science, social psychology, behavioral economics and decision science demonstrates how individuals process and use information for decision making. This body suggests that the integration of different types of information and values into a decision is a very difficult cognitive process and only a small amount of variables can be processed (Hibbard *et al*, 1997a). (Slovic, 1982) conducted a study were participants were asked to make predictions based on 5, 10, 20 and 40 variables. He discovered that as more information was available, the confidence of participants increased but the reliability of their choices decreased. When individuals had more information, their ability to process it consistently declined. Cognitive psychology explains this phenomenon in terms of cognitive load, which refers to the mental effort to solve a problem. A heavy cognitive load typically creates an error.

A study by (McWilliams *et al*, 2011) demonstrated the heavy cognitive load effect caused by a health plan decision. They studied Medicare Advantage plan choice and found that enrolment decreased when more than thirty plans were available. Retirees didn't enrol due to the heavy cognitive load associated with choosing a plan from a large number of options.

Cognitive Bias

(Johnson, 1993) studied whether biases in probability assessment and perceptions of loss affect consumers' decisions about insurance. They found out that study participants made hypothetical choices that violated basic laws of probability and value and exhibited distortions in their perception of risk and framing effects. In particular, participants were reluctant to purchase policies with higher deductibles in part due to framing the deductible as a segregated loss, which causes loss aversion. Framing is a type of cognitive bias (Tversky, Kahneman, 1974).

Inability to Estimate Health Outcomes

Choosing a plan requires an estimation of future utilization of health services, that is, the type, quantity and cost of services. This of course requires an estimation of probabilities which is not easy to do even in the presence of actual sample data. To estimate future utilization, it's also necessary to estimate the probability that new health conditions, called morbidities, will be acquired during the plan year. Once this utilization is estimated, it can be used to calculate the expected cost for every alternative plan. These calculations require the use of publicly available data and expertise that is outside the reach of all but a small group of individuals.

Simplified Heuristics

(Hibbard *et al*, 1997b) found that consumers have limits on how much information they can readily process and as a result, they simplify the decision process, often eliminating certain choices or details and taking heuristic shortcuts (Tversky, Kahneman, 1974) that may lead to erroneous decisions.

Simplified heuristics explain (Abaluck e*t al*, 2011) finding that elders placed much more weight on plan premiums than on expected out-of-pocket costs. Calculating expected costs require significant effort, so decision makers replaced a complex task with a simpler one: choose the plan with the cheapest premium.

In summary, the problems identified above with the unassisted decision making of health plans are:

- Decision errors caused by complexity, high number of choices and inability to estimate health outcomes.
- Decision errors caused by cognitive bias and simplified heuristics

3 CONSUMER BEHAVIOR, EXISTING DECISION SYSTEMS AND DESIREABLE FEATURES

(Scanlon, 1997) reviewed 35 studies of consumer health plan choice. "Almost all authors found price to have a statistically significant negative effect on the probability of enrolling in a health plan". Consumers also favor plans with better benefits over those with less benefits all else being the same. Some studies found that consumers differ on their choices according to their age, gender and health status. This suggests that consumers need to avoid overweighting price in their decision making.

In the (Johnson *et al*, 2013) only one group, Columbia MBA students, performed reasonably well. When researchers provided calculation aids to the non-MBA groups, the performance of these groups improved to the level of the MBA students. This suggests that tools and a well-organized decision process are desirable, which was corroborated by (Hibbard *et al*, 1997b) Their study suggested the following desirable features in a Decision System: 1) reduction of the processing burden; and 2) a method that rationalizes the process. x

Based on the above research and the issues described in Section 2, we propose the following desirable features in a Decision Support System for Health Plan Selection:

1. Reduce to a minimum the amount of information the user needs to process.
2. Use total estimated cost as the main decision factor as opposed to premium cost alone.
3. Anticipate and help users take risk into consideration.
4. Personalize risk and cost estimation.
5. Guide users step by step through a rational process that involves a small number of recommended plans.

We now evaluate existing Decision Support Systems against the set of desirable features above. Wechose a subset of representative systems that are publicly available.

Table 1 shows which feature each system satisfies. The tools that implement the most desirable features are PBGH/CalPERS and CMS Plan Finder. Checkbook is the only tool that estimates medical utilization and takes risk into consideration. No system guides users step by step through a rational decision process.

4 RECOMMENDER FRAMEWORK BY EXAMPLE

We propose a recommender framework to reduce the causes of non-optimal decision making and address the deficiencies of the existing Decision Support Systems (DSS) for health plan selection.

The recommender framework introduced in this paper was designed to satisfy the five criteria outlined on Section 3. It takes risk into consideration by estimating the total expected cost of each plan at various probability levels. Once the total cost and risk are estimated, it uses key performance indicators (KPIs) like premium and deductible to recommend a small number of Pareto optimal plans that have the minimum expected cost. After the plans are recommended, it allows the user to conduct trade-off analysis between the expected cost and the KPIs. The trade-off analysis is implemented through a critique technique to improve a particular KPI. The user iteratively improves KPIs until he is satisfied with the recommendation

The Framework assumes that the decision maker is an individual adult, not a family, that the individual utilizes only in-network plans and that the medical coverage of each plan is standardized, that is, all plans cover the same health conditions. For simplification purposes, it only considers cost KPIs; quality and availability of providers are not considered although the Framework can be extended to consider these non-cost factors. has the following components:

1. Presentation of plan risk profiles
2. Recommendation based on the total estimated plan cost
3. Trade-off analysis capability
4. Final plan selection

We now explain the recommender framework through an example; the implementation details are described in Sections 5 and 6.

Health plans have many characteristics, most of them related to cost sharing. Table 2 shows the cost of in-network services for two hypothetical health plans. We use in-network cost-sharing because they provide the highest benefits.

Table 1: Evaluation of Existing Decision Support Systems.

System	1.Reduce cognitive load	2.Use total estimated cost	3.Consider risk	4. Personalize	5.Guide users
(eHealthInsurance, 2016) individuals and small business	N	N	N	No health status	N
(PBGH/CalPERS, 2016) California gov. employees, retirees	y	User enters utilization	N	Some health status	N
(Massachusetts Health Connector, 2016) State of Massachusetts residents	Y	N	N	Some health status	N
(CMS Medicare Plan Finder, 2016) Medicare Beneficiaries	Y	User enters utilization	N	Y	N
(Healthcare.gov, 2016) (Anyone)	Y	Low, med, high utilization	N	No health status	N
(Consumer Checkbook, 2016) Federal employees and retirees	N	Y	Y	No health status	N

Table 2: Hypothetical In-network Cost Sharing.

Features	Plan A Cost	Plan F Cost
Annual Premium	$4,140	$5,160
Deductible	4,000	$3,300
Out of Pocket Max	$6,454	$4,310
Primary Care Visit	$25	No charge
Specialist Visit	$35	$35
Diagnostic Service	No charge	No charge
Ambulance	No charge	$50
Emergency Room	30%	$100
Inpatient Facility	$200/admission	10%
Inpatient Physician	No charge	$200
Outpatient Facility	$50	20%
Generic Drug	No charge	$10
Brand Drug	$35	20%

Table 3: Common Morbidities.

High blood pressure
Coronary heart disease
Angina
High cholesterol
Diabetes
Arthritis
Chronic Bronchitis
Asthma
Cancer
.....

Table 3 shows a partial list of common health conditions or morbidities that we use to calculate risk and medical utilization. Morbidities, also called Health Conditions, significantly contribute to the utilization of medical services. In other words, they are the drivers of medical utilization. We adopt the comprehensive set of morbidities from the Medical Expenditure Panel Survey Household Component (MEPS-HC), published in 2013 by the Agency for Healthcare Research and Quality.

At the very start the recommender shows the screen in Figure 1 where the user enters personal information like age, gender and health conditions (morbidities). In our example, the user is a 54-year-old male. For simplicity, only a subset of health conditions is shown.

Based on the personal information extracted in Figure 1, the user is presented with the Exploration Dashboard exemplified in (Figure 2).

The Exploration Dashboard presents five Pareto optimal recommendations including Plan A, which has the minimum total estimated annual cost (TEAC). Plan A is the Reference Plan because the other recommendations use it as a reference.

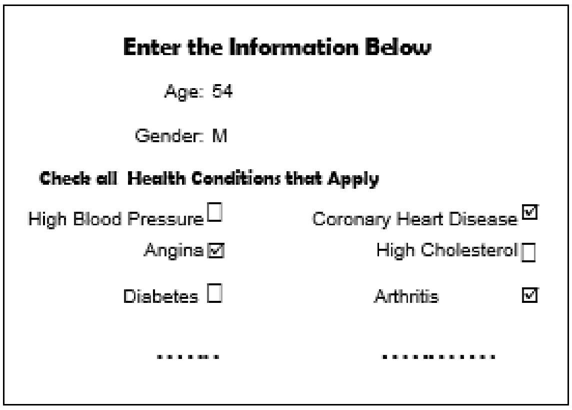

Figure 1: User Input.

The top center panel contains the Trade-off Chart showing the Reference Plan (Plan A) plus four other recommended plans. The x-axis shows the TEAC while the y-axis initially shows the Deductible KPI. Each dot is a plan, with the Reference Plan as the leftmost dot, and the plans are shown in increasing order of TEAC. The four recommended plans from E to H are the plans that have deductibles lower than Plan A and TEAC closest to Plan A.

The recommended plans are Pareto optimal that is, no other KPI, called dimension, can be improved without increasing the TEAC. This means that Plan A's $4,000 deductible cannot be improved without increasing the TEAC, that is, to improve the deductible it's necessary to trade-off TEAC, hence the name Trade-off Chart.

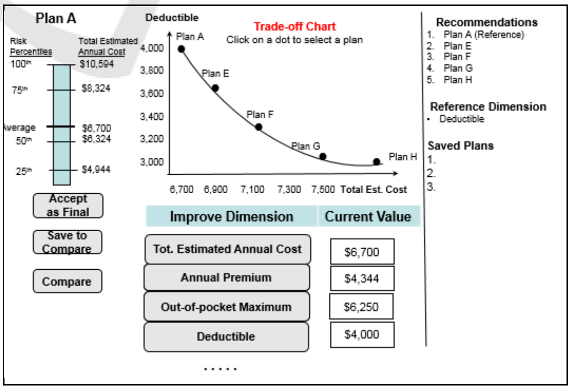

Figure 2: Exploration Dashboard.

The framework deals with the uncertainty of future medical utilization, by estimating the probability distribution of the TEAC. The distribution is showing in the profile bar for Plan A on the top left panel. The left side of the plan profile bar shows quartiles while the right side shows the TEAC for the corresponding quartile. The profile is a proxy for risk. For example, for Plan A, the user has a 25% chance of spending $4,944 during the plan year while the average spending is $6,700. The TEAC is based on: 1) the cost sharing of a particular plan; 2) an estimate of the utilization of medical services and 3) an estimate of the cost of services. The estimations are based on historical data from actual patients with health conditions, age and gender similar to the user.

The lower center panel shows the cost-sharing values for the dimensions of the Reference Plan and come from Table 2. The right panel displays all recommended plans, the chosen reference dimension and the plans saved for comparison if any.

As the name implies, the Exploration Dashboard allows the user to explore different plans, their dimensions and conduct trade-off analysis. The user can:

1. Accept the Reference Plan as the final selection.
2. Save the Reference Plan for comparison.
3. Compare the last three saved plans.
4. Choose another Reference Plan by clicking on the dot corresponding to the desired plan on the chart.
5. Improve (reduce) the value of a particular dimension by clicking on the corresponding button.

Let's say the user wants to improve (reduce) the out-of-pocket maximum. He/she clicks on the button labelled "Out-of-pocket Max" and the system responds by recreating the Trade-off Chart with Out-of-pocket Maximum in the y-axis. The new chart would show the top-5 plans with Out-of-pocket Maximum equal or lower than the Reference Plan.

The Trade-off Chart allows the user to conduct a trade-off analysis prior to making a final selection. It's a trade-off because improving any dimension increases the TEAC because the recommended plans are Pareto optimal.

If the user selects a new Reference plan in the Trade-off Chart, then the profile bar on the left and the bottom center panel are updated to reflect the selected plan.

If the user clicks on the "Compare" button, then the Comparison Dashboard is displayed (Figure 3). It shows the last three saved plans side by side. The top panel displays the profile bars while the bottom panel displays the values for the plan dimensions. The comparison is useful for conducting risk analysis, for example, if a particular user thinks that his medical utilization for the next year will be below average, then Plan A is the optimal plan because it has the lowest total cost for each quartile. On the other hand, if the utilization will be way above average, then Plan F has the optimal risk profile.

The Comparison Dashboard allows the user to accept a particular plan as final or to conduct further analysis by clicking on the Explore button. The idea behind exploration is that the user likes a particular recommendation but wants to further analyze it and perhaps improve some of the plan dimensions.

If the user presses Explore for plan A, the screen in Figure 2 is shown. The process repeats until the user clicks on the "Accept as Final" button in either dashboard.

For an individual with zero medical utilization, the TEAC is just the premium consequently Plan A in Figure 3 is optimal. For an individual with an extremely high utilization, the total cost is the premium plus the out of pocket maximum so Plan F is optimal. For an individual with moderate utilization, the optimal plan usually is the one with the least total cost although the system allows the user to perform a trade-off analysis prior to making the final selection.

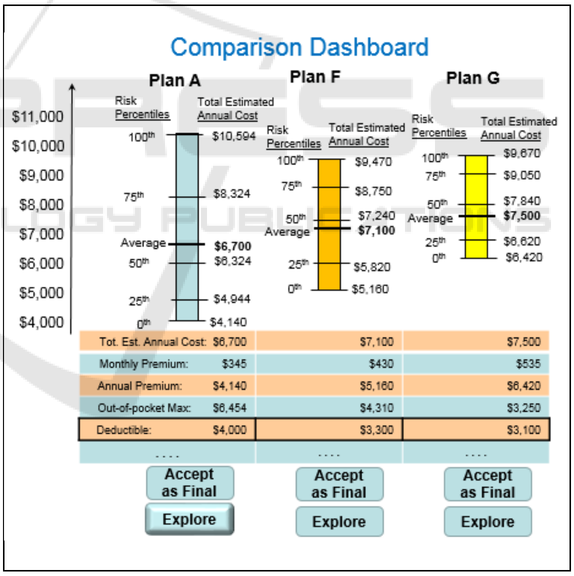

Figure 3: Comparison Dashboard.

5 PERSONALIZED PLAN COST ESTIMATION

The estimation of personalized plan costs is required for the creation of the risk profiles and trade-off charts, which are produced by the system and shown on the Exploration and Comparison Dashboards (Figures 2 and 3).

It is a non-trivial task to estimate the future medical utilization, i.e., medical services like those in Table 2 that the user may need during the health plan period of coverage. To estimate future medical utilization, we need to take into account key drivers such as demographics (age, sex) and health conditions like those in Table 3.

Our approach uses patient historical data to produce a subset of real patients that have health conditions similar to the user. We estimate the cost of a given plan as the average cost of the plan over all patients in the historical database that are similar to the user in terms of his/her medical utilization drivers.

5.1 Data Model

We assume that three datasets exist: 1) historical data from actual patients; 2) cost data from providers; and 3) plan data from insurance companies. We capture these datasets in the model shown in Figure 4. Each relational table is represented by a rectangle with the name above the line and the data elements below. Data elements that are components of the primary key are underlined.

The User and the UserMorbidities tables represent a user of the system while the Plan table represents all insurance plans available to the user. The ActuarialPatients, ActuarialPatientsMorbidities and MedicalVisits tables capture actual patients and their medical utilization, while ProviderServices captures the provider charge for each type of service utilized by the actual patient. The tables with a shaded background are produced by the recommender while the tables with no shade are given.

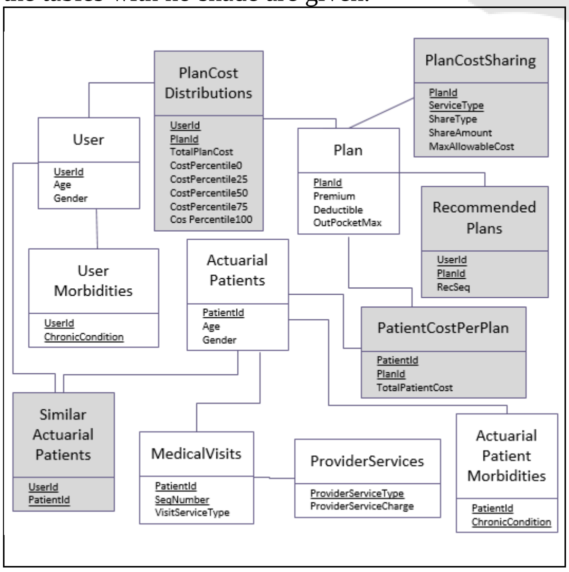

Figure 4: Database Model.

5.2 Data Source

We use two data sources to populate the historical patient data in the recommender database: the Medical Expenditure Panel Survey (MEPS) Household Component (HC) and the Medical Provider Component (MPC) from the Agency for Healthcare Research and Quality. We chose these datasets because they are the most complete source of data on the cost and use of health care and health insurance coverage in the United States. The raw data that we use from the MEPS is shown in Table 4.

Table 4: MEPS-HC and MEPS-MPC Data.

Demographics	Age, gender, …
Chronic Conditions	All in Table 3 and more
Utilization	For each type of service, # of utilizations
Expenditure	For each type of service, total charge by provider

The ActuarialPatients and ActuarialPatientsMorbidities come directly from MEPS-HC while ProviderServices comes from MEPS-MPC.

The MedicalVisits is based on the MEPS-HC but is not a direct mapping. The problem with the raw MEPS-HC dataset is that it does not capture the individual visits to medical providers. Instead, it captures the aggregate number of utilizations for each service type as well as the aggregate cost consequently it cannot be used directly to calculate the total utilization cost. Another issue is that providers calculate cost for each instance of utilization in the order that they occur. We address this problem by averaging two approximations of the medical visits' sequence where the first sequence leads to the minimum cost and the second sequence leads to the maximum cost. This is explained in more detail in subsection 5.3.

5.3 Calculation of Personalized Plan Cost

We now formalize the calculations to estimate personalized plan costs. Personalized means that the estimation is based on attributes of the user of the system.

Given the following:

$u -$ The user id of the person using the system
$age(u) -$ The age for user u
$gender(u) -$ The gender for user u
$CC -$ The set of Chronic Conditions

$CC(u) \subseteq CC -$ The set of chronic conditions for user u
$AP -$ The set of Actuarial Patients
$age(ap) - \forall ap \in AP$, the age for patient ap
$gender(ap) - \forall ap \in AP$, the gender for patient ap
$CC(ap) \subseteq CC - \forall ap \in AP$,
the set of chronic conditions for patient ap
$NoVisits(ap) - \forall ap \in AP$,
the number of visits by ap to receive medical service
$MST -$ The set of Medical Service Types
$vst(ap, v) \subseteq MST - \forall\, v\ 1 \leq v \leq NoVisits(ap), \forall ap \in AP$, the type of medical service received by ap during the vth visit
$PCharge(t) - \forall t \in MST$,
the provider charge for medical service type t
$P -$ The set of Plans
$premium(p) - \forall p \in P$, the premium for plan p
$ded(p) - \forall p \in P$, the deductible for plan p
$OPMax(p) - \forall p \in P$, the out of pocket max for plan p
$ShareType(p, t) \in \{'copay', 'coinsurance'\} - \forall p \in P, \forall t \in MST$,
the type of cost sharing for Plan p and Service Type t
$ShareAmt(p, t) - \forall p \in P, \forall t \in MST$, the share amount for Plan p and Service Type t that the patient is responsible for. For copay, it's a fixed dollar amount while for coinsurance, it's a percentage of the provider cost.
$MaxAllow(p, t)$- $\forall p \in P, \forall t \in MST$,
the maximum allowable cost for Plan p and Service Type t

<u>We want to compute:</u>
$SAP(u) \subseteq AP -$ *The subset of Actuarial Patients* that is similar to the user u
$PatientCost(ap, p) - \forall\, ap \in SAP(u), \forall p \in P$,
the total estimated cost for Plan p for Actuarial Patient ap similar to u
$PlanCost(u, p) - \forall p \in P$,
the total estimated cost for plan p for user u

<u>Computations</u>:

First, we produce the SimilarActuarialPatients table, which is the set of Actuarial Patients similar to the user.

$$SAP(u) = \{ap \in AP \mid age(ap) = age(u) \wedge gender(ap) = gender(u) \wedge CC(ap) = CC(u)\}$$

Note that the user morbidities are given at the beginning of the period of coverage. In the MEPS-HC data, the actuarial morbidities are captured in Round 1 of interviews prior to any medical utilization actually happen. Because both user and actuarial patients' morbidities are ex-ante, we can use the similarity matching equation above.

Second we calculate, for a particular patient, the cost for the visits that do not exceed the deductible. Note that until the deductible is reached, the patient pays the full charge for coinsurance-based services up to the maximum allowed by the plan. The cost for copay-based services is always a flat fee.

For all *ap* in *SAP(u)*,all *p* in *P*,all *v* from *1* to *NoVisits(ap)*,

Case 1: $ShareType(p, vst(ap, v)) =' copay'$
$$PayBefDed(ap, p, v) = ShareAmt(p, vst(ap, v))$$
Case 2: $ShareType(p, vst(ap, v)) \neq 'copay'$
$$PayBefDed(ap, p, v) = min(PCharge(vst(ap, v)), MaxAllow(p, vst(ap, v)))$$
$$CumPayBefDed(ap, p, 0) = 0$$
$$CumPayBefDed(ap, p, v) = CumPayBefDed(ap, p, v-1) + PayBefDed(ap, p, v)$$

Third, we calculate the cost for the first coinsurance visit that exceeds the deductible.

Case 1: $ShareType(p, vst(ap, v)) =' copay' \vee CumPayBefDed(ap, p, v) \leq ded(p)$
$$PayDedAdj(ap, p, v) = PayBefDed(ap, p, v)$$
Case 2: $\neg$Case 1$\wedge$ $CumPayBefDed(ap, p, v-1) \leq ded(p)$
$$PayDedAdj(ap, p, v) = ded(p) - CumPayBefDed(ap, p, v-1) + (CumPayDedAdj(ap, p, v) - (ded(p) - CumPayBefDed(ap, p, v-1))) * ShareAmt(p, vst(ap, v))$$

Fourth, we calculate the cost for the remaining visits that exceed the deductible.

Case 3: $\neg$Case 1$\wedge$ $CumPayBefDed(ap, p, v-1)) > ded(p)$
$$PayDedAdj(ap, p, v) = PayBefDed(ap, p, v) * ShareAmt(p, vst(ap, v))$$
$$CumPayDedAdj(ap, p, 0) = 0$$
$$CumPayDedAdj(ap, p, v) = CumPayDedAdj(ap, p, v-1) + PayDedAdj(ap, p, v)$$

Fifth, we calculate the total estimated cost for all visits for patient *ap*, which is capped by the out of pocket maximum for the plan.

Case 1: $CumPayDedAdj(ap, p, NoVisits(ap) \leq OPMax(p)$
$$PatientCost(ap, p) = CumPayDedAdj(ap, p, NoVisits(ap))$$
Case 2: $CumPayDedAdj(ap, p, NoVisits(ap) > OPMax(p)$
$$PatientCost(ap, p) = OPMax(p)$$

Sixth, we estimate the TEAC for user u, which is the average utilization cost of all similar actuarial patients plus the premium. This result is used to populate the

TotalPlanCost attribute of the PlanCostDistribution table.

$$PlanCost(u,p) = \frac{\left(\sum_{ap \in SAP(u)} PatientCost(ap,p)\right)}{|SAP(u)|} + premium(p)$$

Because the MEPS data does not have the precise sequence of medical visits for an actuarial patient, we create two sequences of *vst(ap,v)*; one that leads to the minimum cost for patient *ap* and another that leads to the maximum cost. The computations above are then performed for each sequence and the results are averaged. This means that the variable *PatientCost(ap,p)* used in the computation of *PlanCost(u,p)* is the average cost of both sequences.

5.4 Plan Risk Profile

Figure 2 and 3 show the risk profile bars for several plans. A profile bar is a proxy for risk. The left side shows quartiles while the right side shows the total estimated annual cost for the corresponding quartile.

Quartiles are percentiles at quarter intervals, in our case 0, 25, 50, 75 and 100. We calculate the distribution of the cost and then the quartile ranks and populate the PlanCostDistribution table.

6 RECOMMENDER FRAMEWORK ARCHITECTURE

The recommender is modelled by the UML Statechart in Figure 5. The system is a constraint-based conversational recommender with two phases. In the first phase (states 1 to 4), the system computes a small number of recommendations while in the second phase (states 5 and 6), it interacts with the user to refine the recommendations in a feedback loop.

In State 1, the system presents the screen in Figure 1 and the user enters his/her age, gender and health conditions (the morbidities in Table 3). In State 2, the system matches the user's age, gender and morbidities to the ActuarialPatients data to determine the set of similar patients and produces the SimilarActuarialPatients table according to the calculations in Section 5.3. The given data in the MEPS-based tables are interpreted as implicit preferences, that is, by using a particular health care service, the MEPS-HC surveyed patients expressed a need, which is a hard preference.

In State 3, the system calculates the actual cost for each plan for each similar patient using the formal model described in Section 5.3. In State 4 step 1, the cost per patient per plan is sorted and the total estimated annual cost for each quartile level is computed for each plan. These various costs comprise the plan risk profiles and these profiles are personalized because they are based on the information the user provided.

In State 4 step 2, the dominated plans are removed from the Personalized Plan database. Given a set of plans P and a set of dimensions D, we say that plan $p \in P$ is dominated if it can be improved in at least one dimension without sacrificing any other dimension, i.e.,

$$(\exists\, p' \in P)(\exists d \in D)(p' \succ_{d} p \wedge (\forall d' \in D \wedge d' \neq d) p' \succcurlyeq_{d'} p)$$

Where $p' \succ_{d} p$ means strictly better on

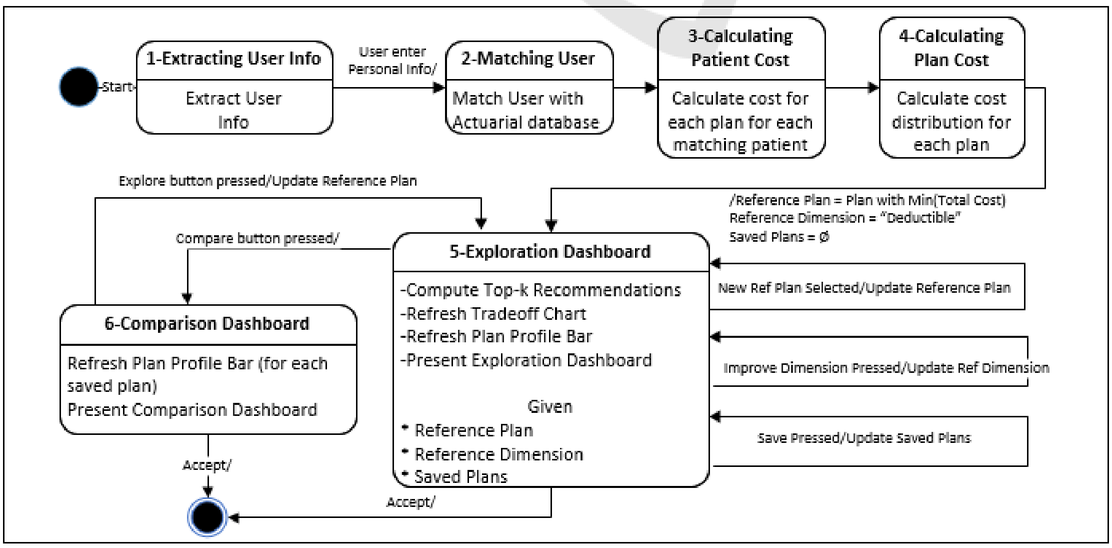

Figure 5: Recommender System UML Statechart.

dimension d and $p' \succcurlyeq_{d'} p$ means better or equivalent on dimension d'.

In State 4 step 3, the top plan, namely the Reference Plan, is calculated. The top plan is the plan with the minimum Total Estimated Annual Cost. The Reference Dimension is set as “Deductible” while the set of Saved Plans is initialized as null. From State 4 on, the state of the system is determined by the following state variables: Reference Plan, Reference Dimension and Saved Plans.

State 5 is the Exploration Dashboard, which is the core of the system. Upon entry to the Exploration Dashboard, the system:

1. Computes the top-5 recommendations.
2. Refreshes the Trade-off Chart.
3. Refreshes the Plan Profile Bar.
4. Presents the Exploration Dashboard (Figure 2).

The computation of the top-5 recommended plans in State 5 step 1 is as follows:

1. Top recommendation r_0 = Reference Plan
2. For every i = 1 to 4, r_i is the plan with the lowest total expected cost higher than r_0 and r_i (reference dimension) $\leq r_0$ (reference dimension)

The top-5 recommendations are Pareto optimal because all dominated plans were removed in State 4 step 2.

In State 5 step 2, the system refreshes the trade-off chart. In step 3, it uses the Reference Plan to refresh the plan profile bar and in step 4 it displays the Exploration Dashboard (Figure 2).

From the Exploration Dashboard, if the user clicks the “Accept as Final” button, the process ends. If the user clicks “Save for Compare”, the systems adds the Reference Plan to the set of Saved Plans. If a plan in the Trade-off Chart is clicked, that plan becomes the Reference Plan and the Exploration Dashboard state is entered again, which forces the recalculation of the top-5 recommended plans.

If a dimension button is pressed, the Reference Dimension is updated and the Exploration Dashboard state is re-entered. Pressing a dimension button critiques the corresponding dimension, that is, improves it. Because the recommended plan is Pareto optimal, there is no other plan that has a lower total cost for the same dimension, consequently the user has to trade-off a lower dimension for a certain increase in the TEAC.

If the “Compare” button is pressed the system then enters State 6, the Comparison Dashboard. Upon entry to the Comparison Dashboard, the system refreshes the Plan Profile Bar for each saved plan and then presents the Compare Dashboard (Figure 3). The top panel displays the profile bars while the bottom panel displays the values for the plan dimensions. The comparison is useful for conducting risk analysis.

From the Comparison Dashboard, if the user clicks on “Explore”, the plan selected is set as the Reference Plan and the system enters the Exploration Dashboard state. If the user clicks the “Accept as Final” button, the Reference Plan becomes the chosen plan and the process ends.

7 CONCLUSION

This paper proposes OptiHealth, a recommender framework for the selection of Pareto optimal health insurance plans. OptiHealth was designed to overcome the main causes of human errors or biases as well as the limitations of current Decision Support Systems. The recommender uses actuarial data to estimate the total annual cost for each plan and then recommends a small number of Pareto optimal plans. It allows the decision maker to iteratively critique specific parameters of a plan, and presents alternatives that improve the critiqued parameters while minimizing the increase of the expected cost. The iterative critique process guides the decision-maker to the preferred trade-off among Pareto optimal alternatives.

We claim that the proposed recommender framework achieves the five desirable features. It 1) reduces cognitive overload; 2) uses total estimated cost as the main decision factor; 3) takes risk into consideration; 4) personalizes risk and total cost; and 5) guides users through a rational process that involves a small number of recommended Pareto optimal plans.

Future research could improve the similarity matching formula by allowing patients that have similar but not identical morbidities, use a range of ages instead of a single one and use other demographic parameters. Other improvements would be to generalize the Framework to handle an entire family instead of a single individual and to relax the assumption that all plans have the same coverage. Future research also could develop a prototype of the recommender.

REFERENCES

Abaluck, J., Gruber, J., 2011. Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. *American Economic Review,* 101(4): 1180-1210.

CMS Medicare Plan Finder, 2016. https://www.medicare.gov/find-a-plan/questions/home.aspx

Consumer Checkbook, 2016. https://www.checkbook.org/newhig2/hig.cfm

eHealthInsurance, 2016. https://www.ehealthinsurance.com/

Frakt, A., 2014. Choosing a Health Plan is Hard, Even for a Health Economist (me). *The Incidental Economist blog*, October 29, 2014.

Heiss, F., Leive, A., McFadden, D., Winter, J., 2013. Plan selection in Medicare Part D: Evidence from administrative data, *Journal of Health Economics, Elsevier*, vol. 32(6), pages 1325-1344.

Healthcare.gov, 2016. https://www.healthcare.gov/

Hibbard, J., Jewett, J., Legnini, M., Tusler, M., 1997a. Choosing A Health Plan: Do Large Employers Use The Data? *Health Affairs*, vol. 16, no. 6, pp. 172-180.

Hibbard, J., Slovic, P., Jewett, J., 1997b. Informing consumer decisions in health care:implications from decision-making research. *Milbank Quarterly* 75(3):395–414.

Johnson, J., Hershey, J., Meszaros, J., Kunreuther, H., 1993. Framing, probability distortions, insurance decisions. *Journal of Risk and Uncertainty* 7: 35–51.

Johnson, E., Hassin, R., Baker, T., Bajger, A., Treuer, G., 2013. Can Consumers Make Affordable Care Affordable? The Value of Choice Architecture. *PLoS ONE* 8(12): e81521.

Massachusetts Health Connector, 2016.
https://betterhealthconnector.com/

Medical Expenditure Panel Survey, 2013. Agency for Healthcare Research and Quality. U.S. Department of Health & Human Resources.
http://meps.ahrq.gov/mepsweb/

McWilliams, J., Afendulis, Christopher, McGuire, T., Landon B., 2011, Complex Medicare Advantage Choices May Overwhelm Seniors, *Health Affairs*, 2011;30*(9):*1786–94.

PBGH/CalPERS, 2016.
https://calpers2015.chooser2.pbgh.org/

Quincy, L., 2012. What's Behind the Door: Consumer Difficulties Selecting *Health Plans. Health Policy Brief*, January 2012, Consumer Union.

Scanlon, D., Chernew, M., Lave, J., 1997. Consumer Health Plan Choice: Current Knowledge and Future Directions. *Annual Review Public Health* 1997, 18:507-28

Slovic, P., 1982. Toward Understanding and Improving Decisions. *Human Performance and Productivity: Vol. 2, Information Processing and Decision Making*, ed. W.C. Howell and E.A. Fleishman (Hillsdale, N.J.: Erlbaum, 1982), 157–183.

Tversky, A., Kahneman, D., 1974. Judgment under Uncertainty: Heuristics and Biases. *Science* 27 Sep 1974: Vol. 185, Issue 4157, pp. 1124-1131. DOI: 10.1126/science.185.4157.1124.