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Making AI Impactful in Healthcare

Soroush Saghafian

http://scholar.harvard.edu/saghafian

Background: Public Impact Analytics Science Lab (PIAS Lab) at Harvard

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- **Devotion:** advancing and applying the science of analytics for solving societal problems that can have public impact.

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- **Mission:** improving societal outcomes by developing and integrating tools in Operations Research, Machine Learning and Big Data, Decision Making, Statistics, Artificial Intelligence (AI), and related fields.
- **Focus:** various aspects of the healthcare sector.

Partnerships and Collaborations (Outside Harvard)

MGH 1811 MASSACHUSETTS GENERAL HOSPITAL

MyWay digital health

Dana-Farber Cancer Institute

MAYO CLINIC

BROWN Alpert Medical School

Emerging Health consulting

FDA

BRIDGEWEST GROUP

BWH BRIGHAM AND WOMEN'S HOSPITAL

Partnerships and Collaborations (Inside Harvard)

HDSI | Harvard Data Science Initiative

Center for Health Decision Science
Harvard School of Public Health
718 Huntington Avenue, Boston, MA 02115

HARVARD T.H. CHAN SCHOOL OF PUBLIC HEALTH

HARVARD Kennedy School
BELFER CENTER for Science and International Affairs

Harvard John A. Paulson School of Engineering and Applied Sciences

HARVARD Faculty of Arts and Sciences

Statistical Reinforcement Learning Lab at Harvard

Harvard Ph.D. Program in Health Policy

Motivation (Based on Various Collaborations)

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Problem: AI and ML tools are not as impactful as they can be in the medical practice.

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Problem: AI and ML tools are not as impactful as they can be in the medical practice.

Question: How can we enhance AI and ML so they become impactful in practice?

Motivation (Cont'd)

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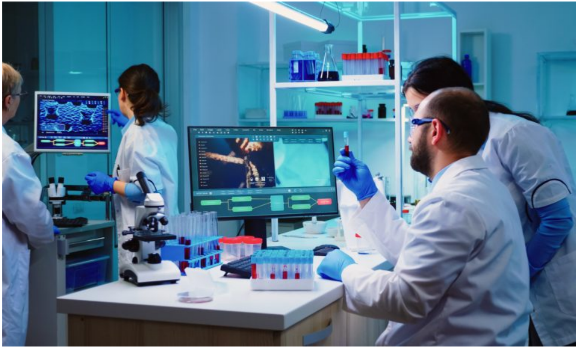
Healthcare Sector Will Devote 10.5% of Spending to AI

BY **PYMNTS**
SEPTEMBER 5, 2023



The healthcare sector is projected to nearly double its spending on artificial intelligence (AI).

A recent report by Morgan Stanley says that the amount allocated to AI and machine learning (ML) in health company budgets is anticipated to be 10.5% next year, compared to 5.5% in 2022. The investment bank says that 94% of healthcare companies are using AI and/or ML in some capacity.

Major Issues (Observations)

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1. Algorithm Aversion: Physicians do not put enough **weight on the advice** from algorithms.
2. Human Aversion: Recommendations from algorithms do not match **physicians' intuition**.
3. Causation Aversion: Algorithms are based on associations between variables (risk prediction) and lack **causal reasoning**. Physicians need help with complex causal reasoning, especial because of inevitable **ambiguity**.

Solution 1: A Centaur Model of AI/ML

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- **AI/ML:** Combining the power of algorithms with human intuition.

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- **Our findings** (experiments at the Mayo Clinic):
  1. Centaurs >> both best **human experts** and strongest algorithms.
  2. Centaurs address both **algorithm aversion** and **human aversion**.

Solution 2: AI/ML for Causal Reasoning under Ambiguity

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Ladder of Causation (Judea Pearl)

Current ML/AI Focus

Where we need to focus

Level (Symbol)	Typical Activity	Typical Questions
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in Y?
2. Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?

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2. **Probabilistic** views $\Rightarrow$ Ignore the fact that physicians:
   - Have to deal with **ambiguity (Knightian uncertainty)**
   - Have different **ambiguity attitudes**

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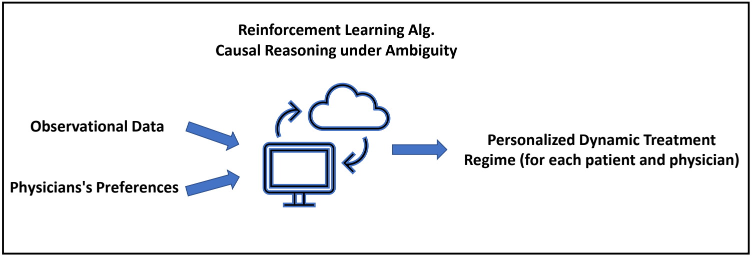

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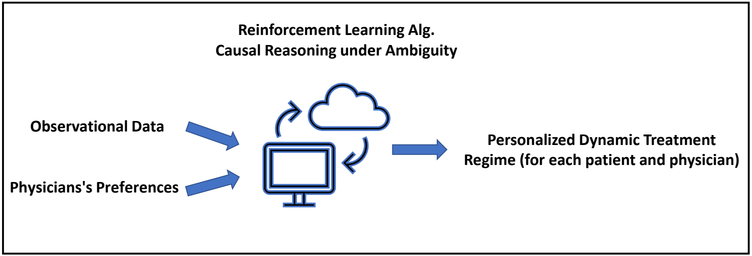

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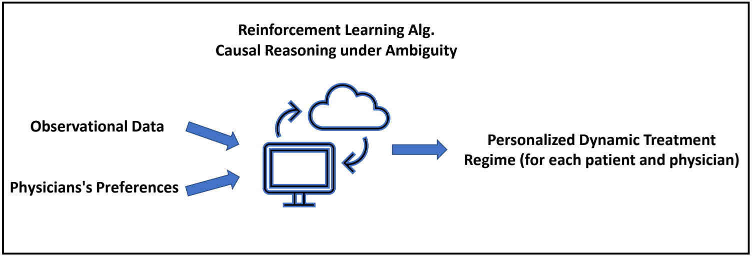

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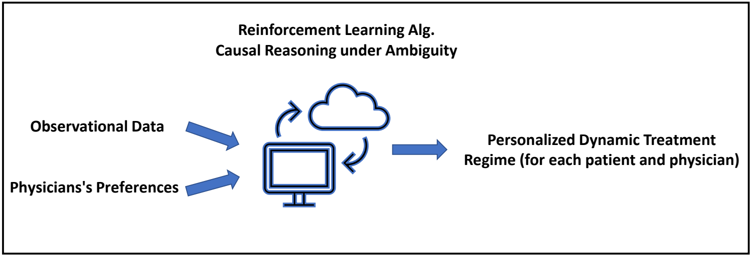

- **Our findings** (experiments at the Mayo Clinic):
  1. Generates superior treatment regimes: yield causal improvements.
  2. Allows for two-way personalization: personalization based on both patient and physician characteristics.

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Solution 1 Experiments: Predicting readmissions after solid organ transplantation (kidney, liver, heart)

Study Design

Study Design

I. Data

- A retrospective dataset from the Mayo Clinic was collected.
- Data included large sample of patients with liver, kidney, or heart transplantation.

2. Machine Learning

- Developed and validated a machine learning model that predicts readmission across all solid organ transplant patients.
- Derived actionable clinical insights per organ.

3. Online Survey

- Designed an online survey tool to compare the assessment of human experts versus the machine learning model.
- Tailored to gather individual feedback on the accuracy, clinical drivers of risk, and operational impact of the readmission score.

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  - Weight on advice: 36.33%
- **Centaur's** out-of-sample AUC: 86.46%

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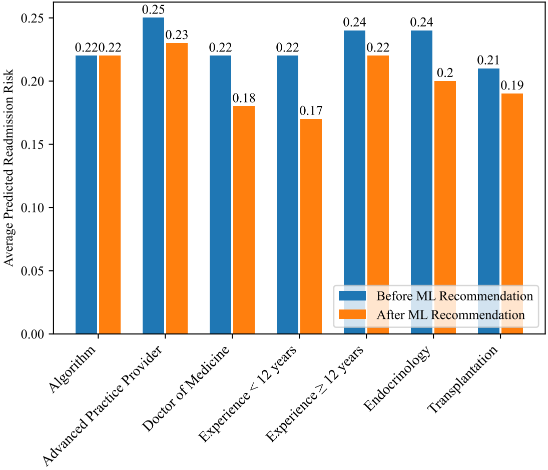

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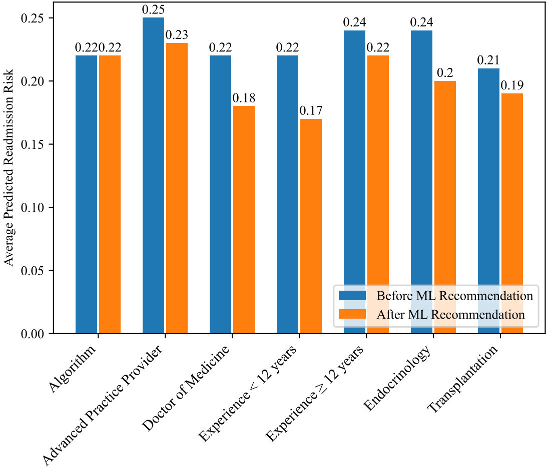

Observation: physicians mainly overestimate the risk; they are conservative.

What Features Are Important: Physicians vs. ML

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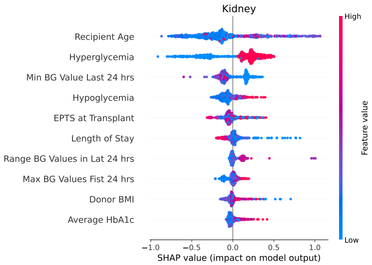
ML



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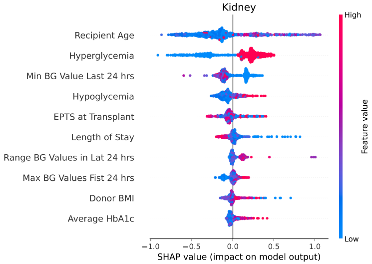
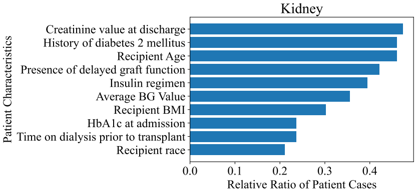


Physicians



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Questions: What would you change in patient care if you knew the patient is at hight risk of readmission?

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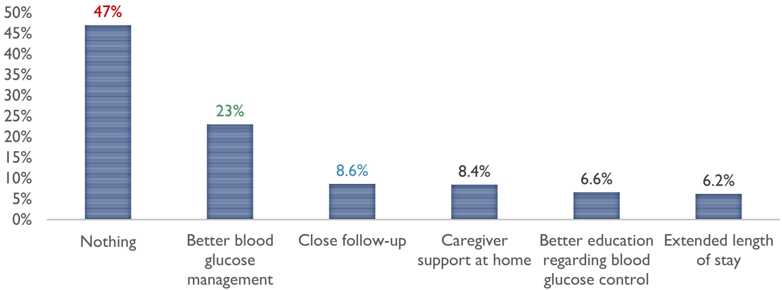

Summary (Solution 1 Experiments)

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- The performance of the ML model was significantly more accurate than the experts
- ML models places more emphasis on factors that differ from the medical intuition
- Physicians rarely take into account the ML model prediction.
  ML recommendations improve the clinical risk perception but it is still outperformed
- When ML uses human intuition as an input, even if it is not very accurate, its performance improves.

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Observation: main suggested change after "nothing:" better glucose management.

Solution 2 Experiments: Improving outcomes for patients who undergo solid organ transplantation (kidney, liver, heart)

Significant Concern: New-Onset Diabetes After Transplantation (NODAT)

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NODAT: Incidence of diabetes in patients with no history of diabetes prior to transplantation.

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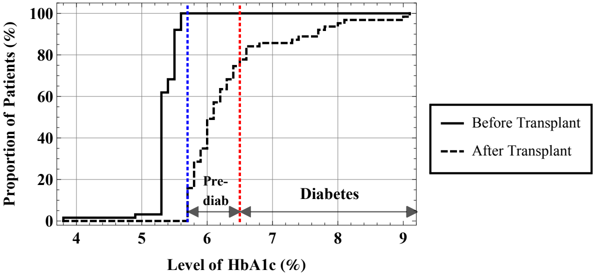

Figure: The left (right) vertical dotted line: the threshold for prediabetes (diabetes) as defined by American Diabetes Association (2012).

New-Onset Diabetes After Transplantation (NODAT)

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ORIGINAL PAPER

e-ISSN 2329-0358
© Ann Transplant, 2021; 26: e928624
DOI: 10.12659/AOT.928624

Received: 2020.09.17
Accepted: 2021.01.06
Available online: 2021.02.10
Published: 2021.03.16

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RESEARCH ARTICLE

Characterization of Remitting and Relapsing Hyperglycemia in Post-Renal-Transplant Recipients

Alireza Boloori[1], Soroush Saghafian[2]*, Harini A. Chakkera[3], Curtiss B. Cook[4]

1 Department of Industrial Engineering, School of Computing, Informatics and Decision Systems Engineering, Arizona State University, Tempe, Arizona, United States of America, **2** Harvard Kennedy School, Harvard University, Cambridge, Massachusetts, United States of America, **3** Division of Nephrology and Transplantation, Mayo Clinic School of Medicine, Scottsdale, Arizona, United States of America, **4** Division of Endocrinology, Mayo Clinic School of Medicine, Scottsdale, Arizona, United States of America

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Incidence, Risk Factors, and Trends for Postheart Transplantation Diabetes Mellitus

Check for updates

Vidit N. Munshi, MA[a,*], Soroush Saghafian, PhD[b], Curtiss B. Cook, MD[c], D. Eric Steidley, MD[c], Brian Hardaway, MD[c], and Harini A. Chakkera, MD, MPH[c]

Data-Driven Management of Post-transplant Medications: An Ambiguous Partially Observable Markov Decision Process Approach

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New-Onset Diabetes After Transplantation (NODAT)

MAYO CLINIC

National Science Foundation

ANNALS OF TRANSPLANTATION
ORIGINAL PAPER
e-ISSN 2329-0358
© Ann Transplant, 2021; 26: e928624
DOI: 10.12659/AOT.928624
Received: 2020.09.17
Accepted: 2021.01.06
Available online: 2021.02.10
Published: 2021.03.16

Use of Imputation and Decision Modeling to Improve Diagnosis and Management of Patients at Risk for New-Onset Diabetes After Transplantation

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RESEARCH ARTICLE

Comparison of post-transplantation diabetes mellitus incidence and risk factors between kidney and liver transplantation patients

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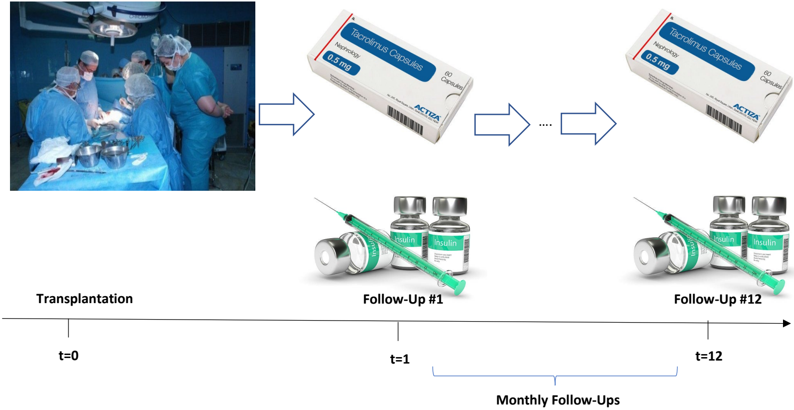
- **Disadvantage:** diabetogenic effect (cause elevation in blood glucose).

Monthly Follow-Ups



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Example: Mobile Health (mHealth) Applications

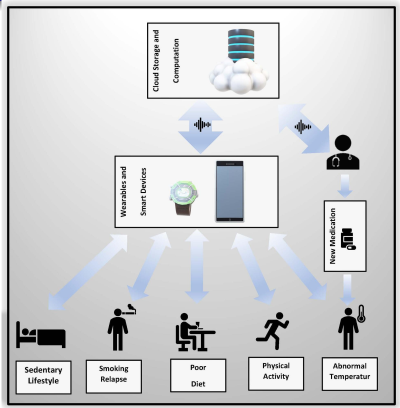

Figure: mHealth Ecosystem (Saghafian & Murphy, 2021*)

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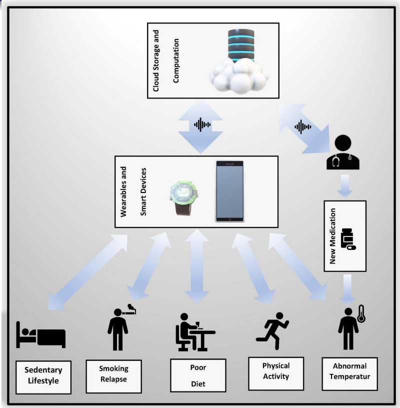

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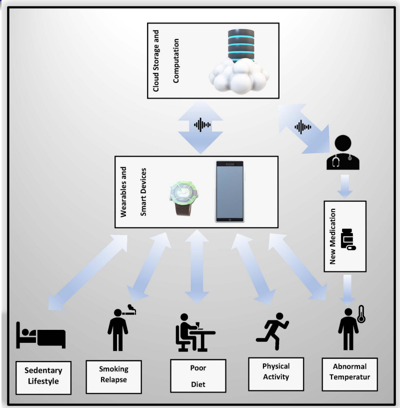

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- **Goal:** studying the effect of users following a treatment regime and not just being assigned to it; Data might be experimental (e.g., MRT)
- **Unobserved Time-Varying Confounders:** user habituation, engagement, and/or compliance.

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Observed Covariates

Table: Observed Covariates (at each follow-up)

Var. No.	Risk Factor (Abbr.)	Unit	Low Level	Mid Level	High Level	Time-Varying
1	Glucose test† (FPG, HbA1c)	mg/dL, %	Healthy	Pre-Diabetic	Diabetic	Yes
2	Trough level test‡ (C_0)	mg/dL	[4, 8)	[8, 10)	[10, 14]	Yes
3	Age	Years	<50	—	$\geq$ 50	No
4	Gender	—	Female	—	Male	No
5	Race	—	White	—	non-White	No
6	Diabetes history (Diab Hist)	—	No	—	Yes	No
7	Body mass index (BMI)	kg/m^2	<30 (non-obese)	—	$\geq$30 (obese)	Yes
8	Blood pressure (BP)	—	Normal♯	—	Hypertension	Yes
9	Total cholesterol (Chol)	mg/dL	<200	—	$\geq$200	Yes
10	High-density lipoportein (HDL)	mg/dL	$\geq$40	—	<40	Yes
11	Low-density lipoportein (LDL)	mg/dL	<130	—	$\geq$130	Yes
12	Triglyceride (TG)	mg/dL	<150	—	$\geq$150	Yes
13	Uric acid (UA)	mg/dL	<7.3	—	$\geq$7.3	Yes

†A patient with FPG$\geq$126 (100 $\leq$FPG< 126) mg/dL or HbA1c$\geq$6.5% (5.7 $\leq$HbA1c<6.5%) is labeled as diabetic (pre-diabetic), and a patient with FPG<100 mg/dL or HbA1c<5.7% is labeled as healthy (ADA 2012).

‡$C_0 \in$ [4, 8), [8, 10), [10, 14] mg/dL is label as "low," "medium," and "high," respectively.

♯Normal Blood Pressure (BP) is defined as systolic (diastolic) BP less than 120 (80) mmHg.

Note: All variables with three levels are coded as 1,2, 3 (low, mid, high). All variables with two levels are coded as 1, 2 (low, high).

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- We can study ADTRs using APOMDPs (Saghafian 2018*).
- This allows us to develop Reinforcement Learning approaches to learn the optimal treatment policy.

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Direct Augmented V-Learning (DAV-Learning)

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Algorithm 1: `DAV-Learning`

for *each observed trajectory and model* $m \in \mathscr{M}$ **do**
- Initialize $\boldsymbol{\pi}_0^m$ using a random draw from $F(\boldsymbol{\pi})$;
- set t=1;
- **while** $t+1 \in \mathscr{T}$ **do**
  - $\boldsymbol{\pi}_{t+1}^m \leftarrow T(\boldsymbol{\pi}_t^m, a_t, o_t, m)$;

for *any given* $\boldsymbol{\mu}^e \in \Upsilon$ *and* $m \in \mathscr{M}$ **do**
- $\varphi_n^{m,\boldsymbol{\mu}^e}(\boldsymbol{\psi}) \leftarrow \mathbb{E}^{\mathbb{P}}\left[\sum_{t\in\mathscr{T}}\left[\frac{\mu^e(A_t|\boldsymbol{\Pi}_t^m)}{\mu^b(A_t|\boldsymbol{\Pi}_t^m)}\left[G_t + \beta V_\infty^{m,\boldsymbol{\mu}^e}(T(\boldsymbol{\Pi}_t^m, A_t, O_t, m)) - V_\infty^{m,\boldsymbol{\mu}^e}(\boldsymbol{\Pi}_t^m)\right]\mathbf{b}(\boldsymbol{\Pi}_t^m)\right]\right]$;
- $\hat{\boldsymbol{\psi}}_n^{m,\boldsymbol{\mu}^e} \leftarrow \operatorname{argmin}_{\boldsymbol{\psi}\in\boldsymbol{\Psi}}\left\{\left(\varphi_n^{m,\boldsymbol{\mu}^e}(\boldsymbol{\psi})\right)' \boldsymbol{\Omega}\, \varphi_n^{m,\boldsymbol{\mu}^e}(\boldsymbol{\psi}) + \theta_n \mathcal{P}(\boldsymbol{\psi})\right\}$;
- $\hat{V}_\infty^{m,\boldsymbol{\mu}^e}(\boldsymbol{\pi}) \leftarrow \left(\mathbf{b}(\boldsymbol{\pi})\right)' \hat{\boldsymbol{\psi}}_n^{m,\boldsymbol{\mu}^e}$;
- $\hat{\Gamma}_\infty^m(\boldsymbol{\mu}^e) \leftarrow \int \hat{V}_\infty^{m,\boldsymbol{\mu}^e}(\boldsymbol{\pi})\, dF(\boldsymbol{\pi})$;

for *any given* $\boldsymbol{\mu}^e \in \Upsilon$ **do**
- $\hat{\Gamma}_\infty(\boldsymbol{\mu}^e) \leftarrow \alpha \inf_{m\in\mathscr{M}} \hat{\Gamma}_\infty^m(\boldsymbol{\mu}^e) + (1-\alpha)\sup_{m\in\mathscr{M}} \hat{\Gamma}_\infty^m(\boldsymbol{\mu}^e)$;

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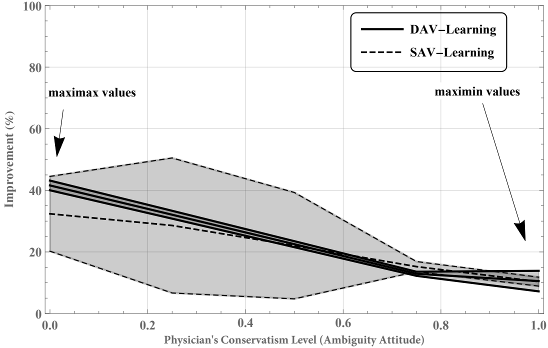

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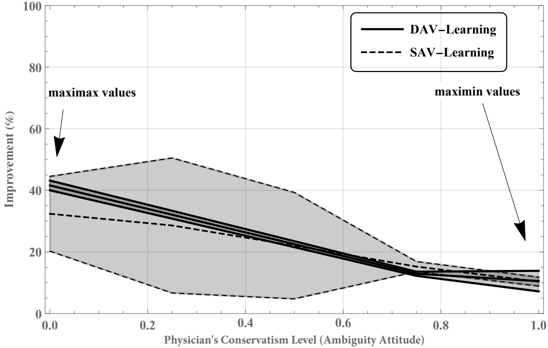

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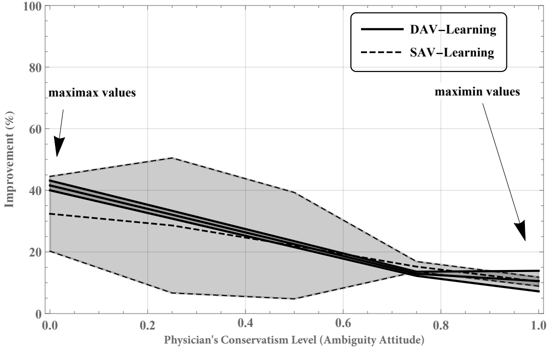

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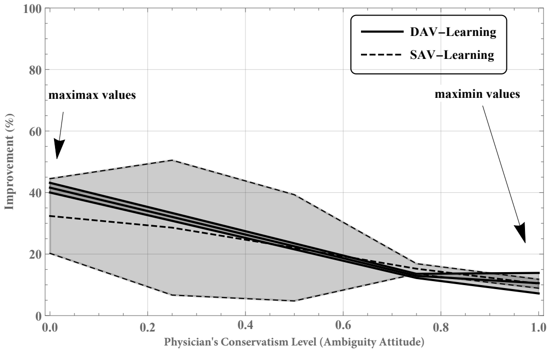

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* Large-scale grant from DoD (Congressionally Directed Medical Research Programs), and collaborations with DFCI and Brigham and Women Hospital.

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Thank You!

Soroush Saghafian

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