University of California
San Francisco

Using the EHR and data science to change how we deliver healthcare

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My Journey

My Journey

My Journey

NIS Overview

The National (Nationwide) Inpatient Sample (NIS) is a set of longitudinal hospital inpatient databases included in the HCUP family. These databases are created by AHRQ through a Federal-State-Industry partnership.

HHS Public Access
Author manuscript
Arthritis Care Res (Hoboken). Author manuscript; available in PMC 2016 May 01.

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Arthritis Care Res (Hoboken). 2015 May ; 67(5): 673–680. doi:10.1002/acr.22501.

Infection is the leading cause of hospital mortality in patients with dermatomyositis/polymyositis: data from a population-based study

Sara G. Murray, MD[1], Gabriela Schmajuk, MD, MSc.[2], Laura Trupin, MPH[1], Erica Lawson, MD[3], Matthew Cascino, MD[1], Jennifer Barton, MD[1], Mary Margaretten, MD[1], Patricia P. Katz, PhD[1,4], Edward H. Yelin, PhD[1,4], and Jinoos Yazdany, MD, MPH[1,4]

Arthritis Care & Research
American College of Rheumatology
Empowering Rheumatology Professionals

Ankylosing Spondylitis | Free Access

Cervical Spinal Fracture and Other Diagnoses Associated With Mortality in Hospitalized Ankylosing Spondylitis Patients

Katherine D. Wysham, Sara G. Murray, Nancy Hills, Edward Yelin, Lianne S. Gensler

First published: 09 May 2016 | https://doi.org/10.1002/acr.22934 | Cited by: 4

PLOS | ONE

RESEARCH ARTICLE

National Lupus Hospitalization Trends Reveal Rising Rates of Herpes Zoster and Declines in Pneumocystis Pneumonia

Sara G. Murray[1]*, Gabriela Schmajuk[1,2], Laura Trupin[1], Lianne Gensler[1], Patricia P. Katz[1,3], Edward H. Yelin[1,3], Stuart A. Gansky[4], Jinoos Yazdany[1,3]

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CrossMark

My Journey

UCSF

My Career / Training

Associate Chief Medical Information Officer, UCSF Health – Board Certification in Clinical Informatics (now a fellowship)

Direct the Advanced Analytics and Innovation Team – Master's in Clinical Research

Practicing Hospitalist at UCSF , MD, Internal Medicine Residency, Board Certification in Internal Medicine

Roadmap

- **Causal inference in EHR data**
- Using new data creatively
  - Spatial and temporal tracking of *C. difficile*
  - Reducing clerical work for trainees by automating work hours
- Artificial intelligence and ethical issues

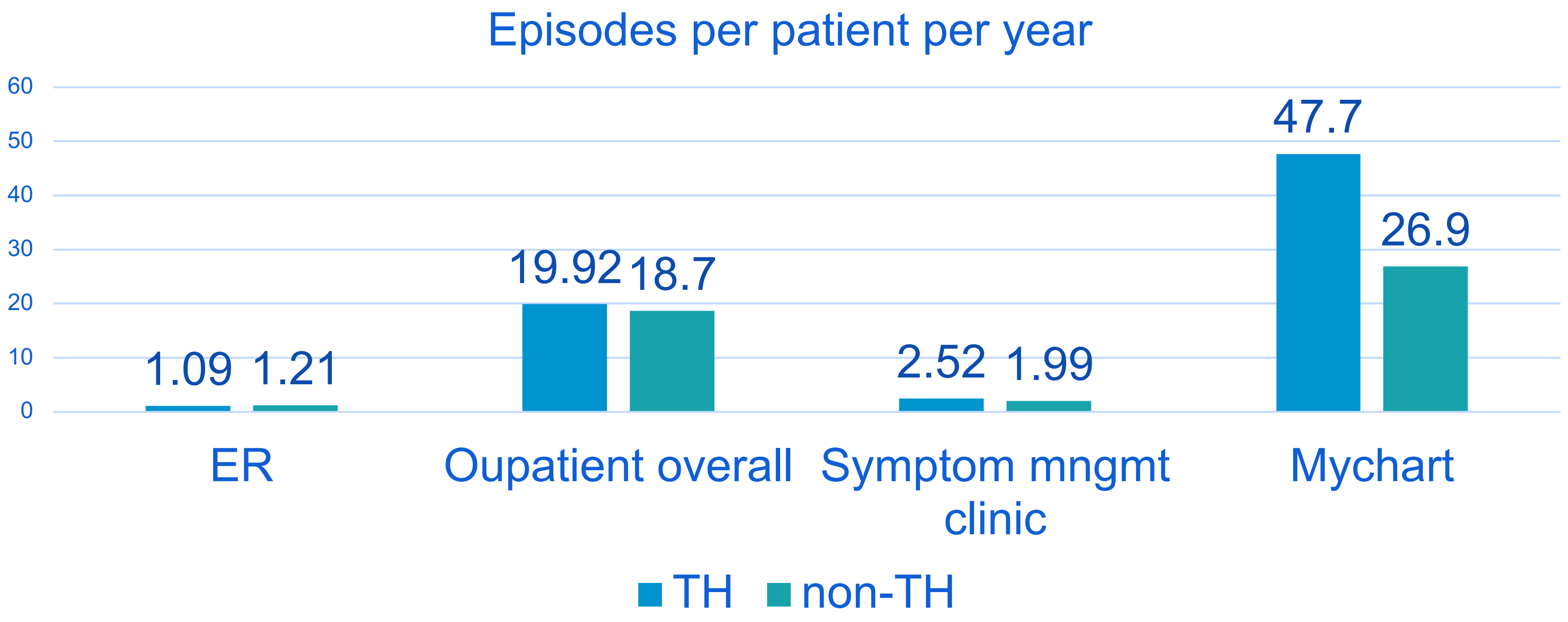
UCSF

Let's pretend it's pre-pandemic

- We're leaders in telehealth, doing 2.5% of our visits virtually
- We're unique in that we offer telehealth to all patients regardless of whether their insurance reimburses
- We're in a position to ask the important question of whether provisioning telehealth decreases excess healthcare utilization

Does telehealth utilization prevent ED visits? Reduce mychart messages?

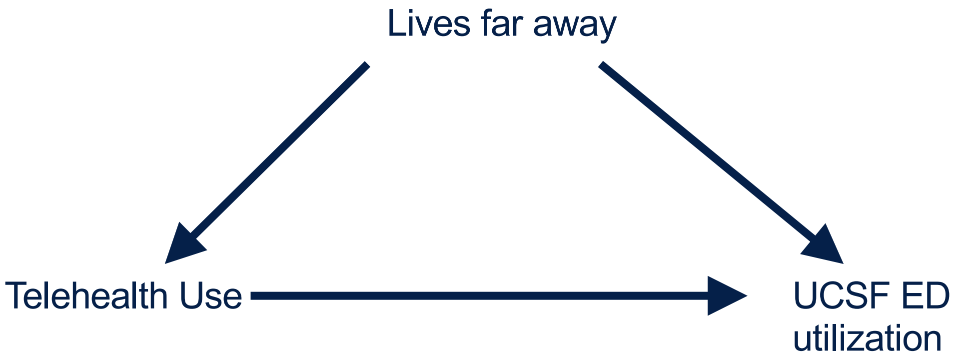
Symptom Management Clinic



Is telehealth reducing ED visits?

Telehealth Use → UCSF ED utilization

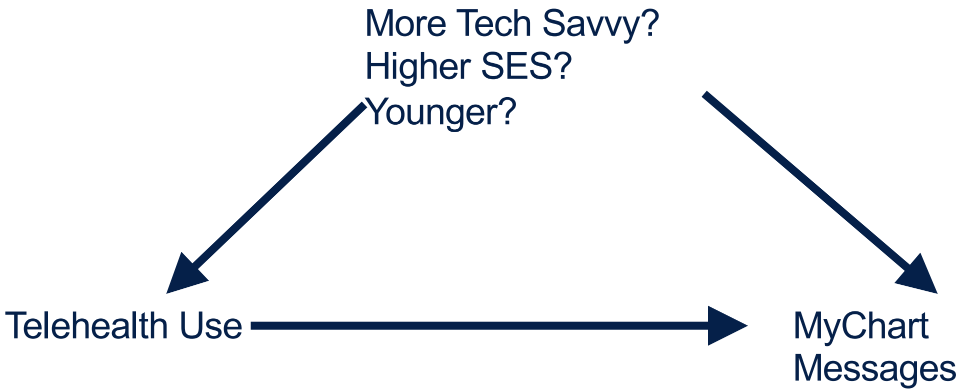
Is telehealth reducing ED visits?



Is telehealth increasing MyChart messaging?

Telehealth Use → MyChart Messages

Is telehealth increasing MyChart messaging?



Why am I showing you this example?

- Basic principles that you learned in biostats and epidemiology remain critically important when you work with EHR data
  - They don’t go away just because you built a ML model!
- Think through any

Roadmap

- Causal inference in EHR data
- Using new data creatively
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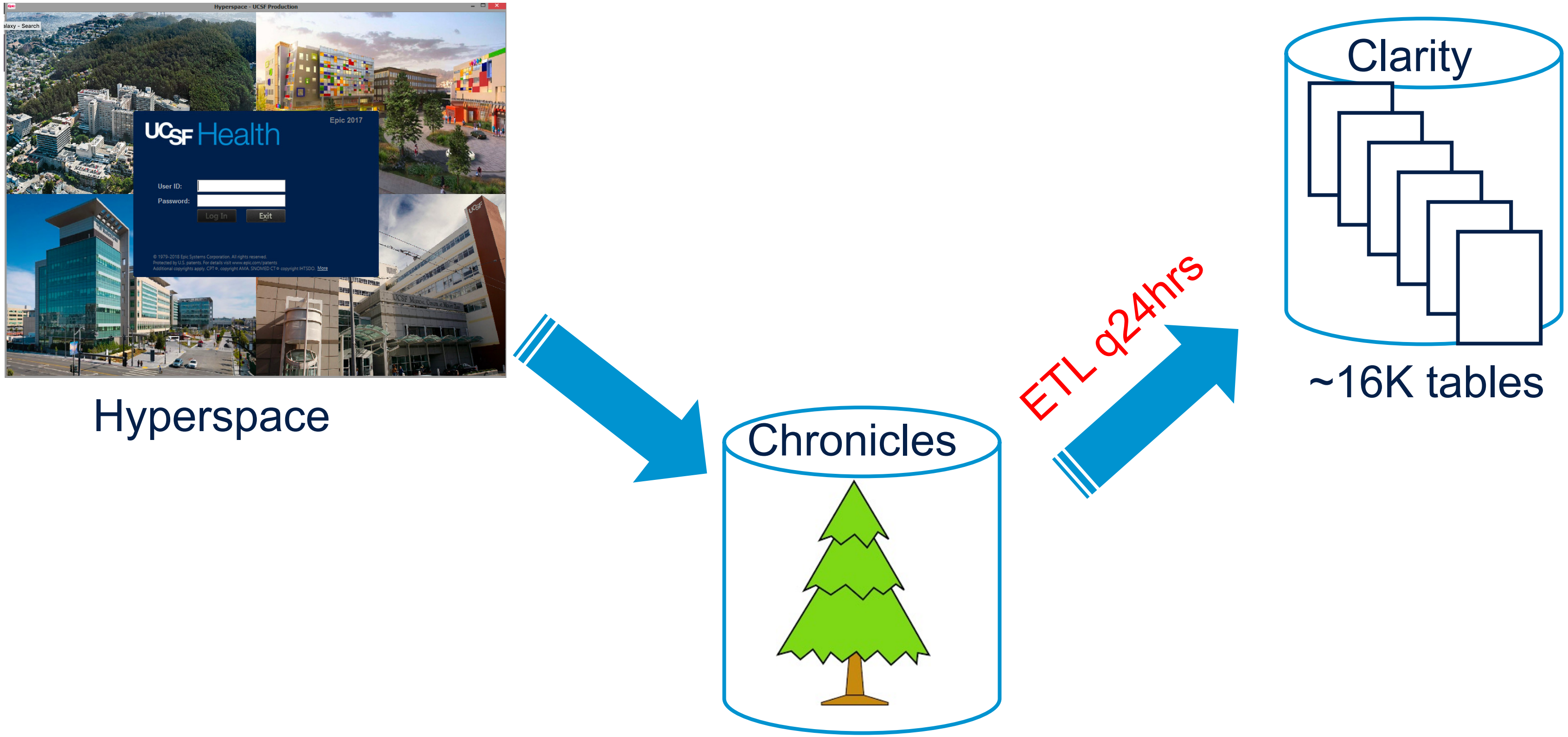
UCSF

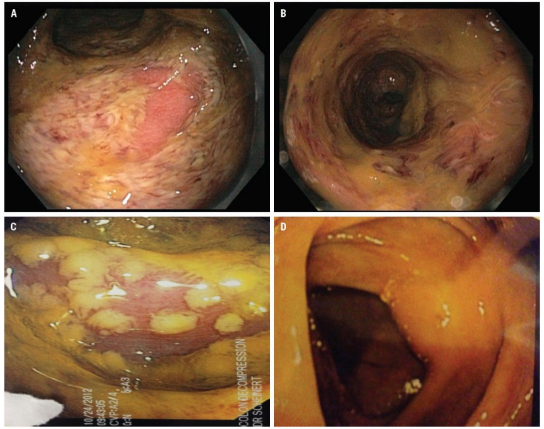
Epic EHR data 101



Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

- *C. difficile* is a serious hospital-acquired diarrheal illness associated with morbidity and death
- Spores live on surfaces for long periods and are difficult to clean



Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

- 2016: UCSF Medical Center goal to reduce our rate of hospital acquired *C. difficile*
  - Handwashing and appropriate contact precautions campaign
  - Antimicrobial stewardship
  - Improved protocols for test ordering and treatment
- ***Can we use data to figure out whether there are spaces that are being inadequately cleaned?***

Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

Does exposure to a physical space in the hospital which was previously visited by a *C. difficile*-infected patient (within 24 hours) increase your risk of *C. difficile* infection?

- Example:

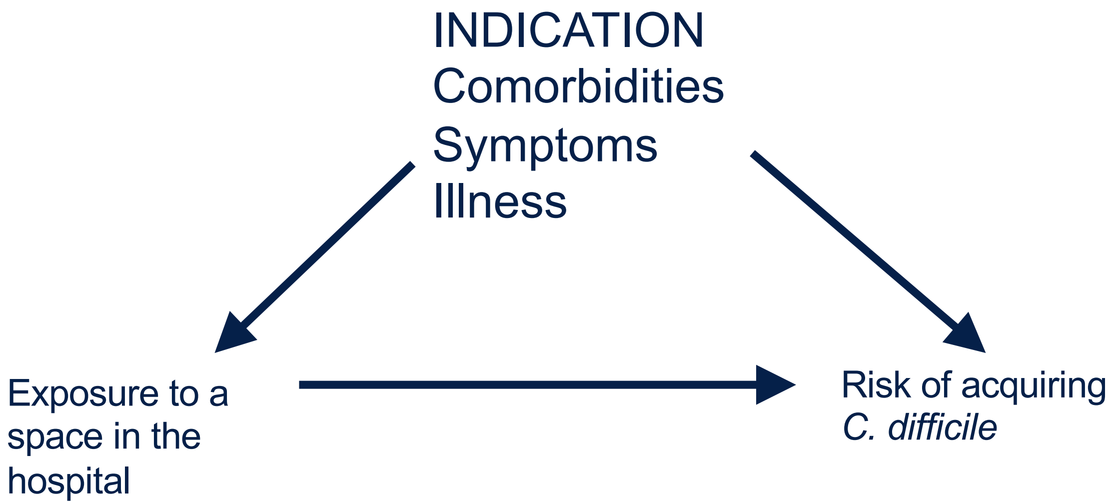
  1. Emily is in ED room 26 with *C. difficile,* prior to being admitted to a hospital floor upstairs
  2. Manny is then roomed in ED room 26 after Emily
  3. Is Manny's chance of developing *C. difficile* within the next 60 days higher than Sara's, who also came to the ED but didn't spend time in a space recently occupied by someone with *C. difficile?*

Confounding POP QUIZ

- Why can’t I just look at the rates of *C. difficile* in different spaces in the hospital? Why do I need to compare to other patient who went through the same space at a different time?

Exposure to a space in the hospital → Risk of acquiring *C. difficile*

Confounding POP QUIZ



Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

- We analyzed every hospitalized patient and every location change from 1/2013 through 12/2015
  - 53,249 unique patients admitted to the hospital
  - 86,648 hospitalizations
  - 434,745 location changes in the hospital
  - 1,152 cases of laboratory-documented *C. difficile* in the inpatient setting or within 60 days of discharge at UCSF

Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

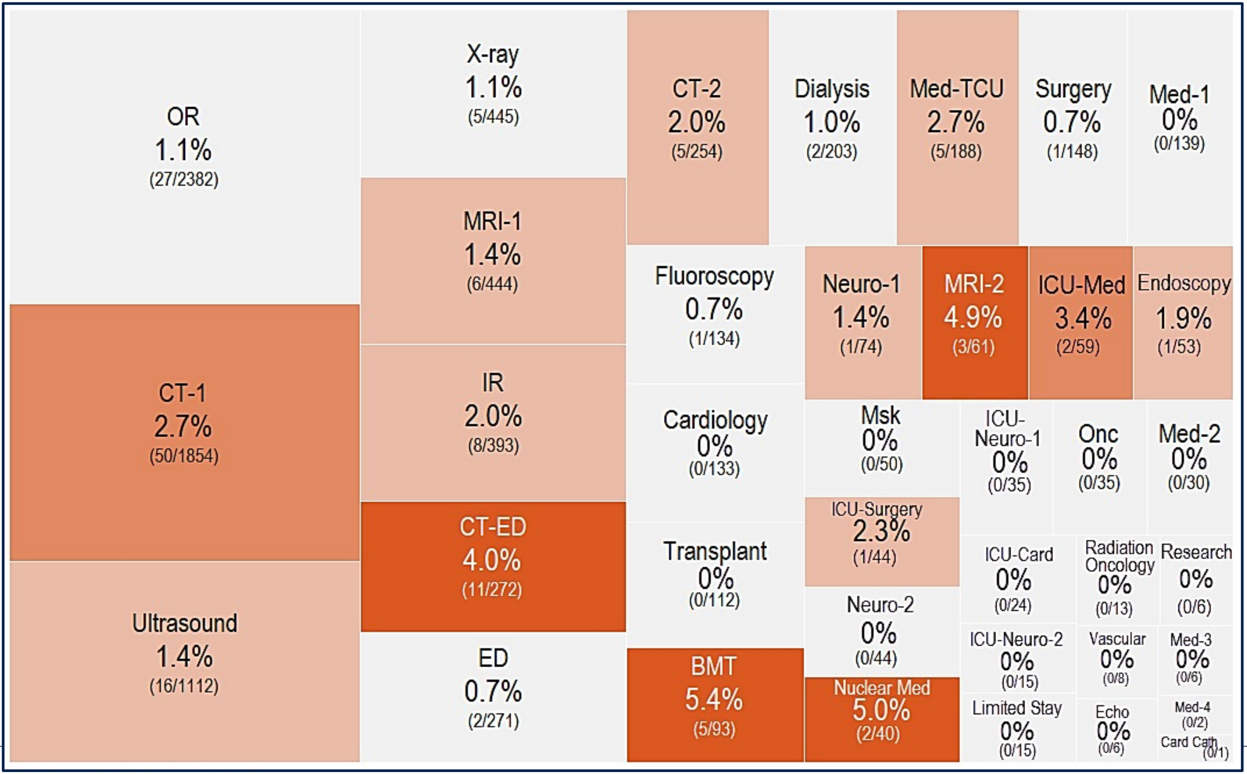
Hospital wards

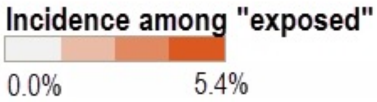
Other areas

Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

Areas in hospital where “exposure” conferred risk





Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

Getting a CT scan in the ED within 24 hours after a patient with *C. difficile* used the scanner was associated with a **2.5 fold** increased odds of disease in comparison to getting that same CT when the scanner was not considered potentially “contaminated”.

Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

Getting a CT scan in the ED within 24 hours after a patient with *C. difficile* used the scanner was associated with a **2.5 fold** increased odds of disease in comparison to getting that same CT when the scanner was not considered potentially “contaminated”.

Quality Improvement Executive Committee & Infection Control → Investigation → Who’s cleaning it?

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Tracking disease spread in the hospital

Spatial and temporal mapping of *C. difficile*

New protocols to ensure the room was being cleaned between patients were put into place in January 2017

January 2017 – January 2019: Rate among ”exposed” = 0.07%

(2.3% in “unexposed”)

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Roadmap

- Causal inference in EHR data
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- Artificial intelligence and ethical issues

Residency Work Hours

- Accreditation Council for Graduate Medical Education (ACGME) sets guidelines
  - Work hours must not exceed 80 hours per week, averaged over a four-week period
  - Additional limits are imposed on shift duration, time off between shift, and 1 day off in 7
  - Programs in violation of regulations are at risk for citation and loss of accreditation

- While violations are currently self-reported in an annual survey, programs have the duty to ensure timely collection of work hour data
  - *MedHub*

Self-report is Inconsistent and Biased

- 1 out 3 internal medicine trainees self-report for less than 50% of their UCSF work days. (Avg. report rate 65%)
- MedHub data may be delayed by several days to weeks
- There is bias in self-reporting
  - Several studies show residents routinely under-report work hours to appear in compliance; e.g.:
    - Fargen et al. *J Grad Med Educ* (2013) 5 (4): 553–555
    - Drolet et al. *JAMA Surg*. (2013) ;148(5): 427-433
    - Gonzalo et al. *J Grad Med Educ* (2013) 5(4): 630–633

Situation on the Ground

- Residents are already generating massive amounts of data from their daily work

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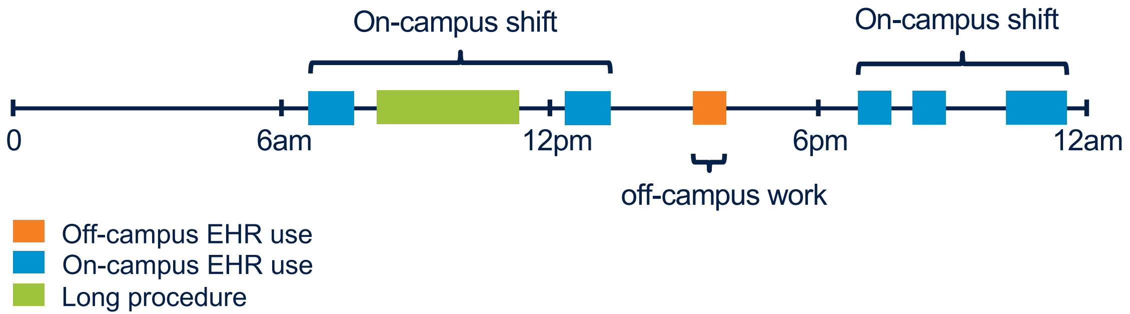
Can we leverage work that is already happening to automate processes and REDUCE CLERICAL WORK that we are requiring of our trainees?

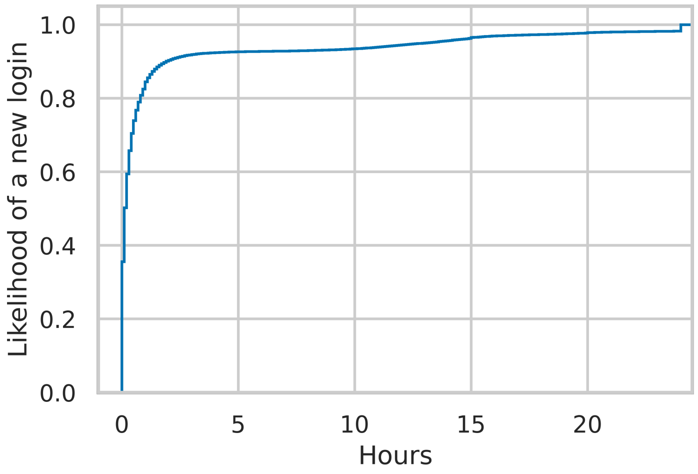
A Data-Driven Approach

- Model that leverages EHR audit log data, procedural data, and routine scheduling data
- Enables us to measure:
    1. Continuous work hours in the hospital (both work done in the EHR and inferred rounding, bedside care, etc.)
    2. Work hours at home in the EHR



How can we estimate work hours using EHR data?

- At any log-out, what is the distribution of time until next log-in?
  - Time-to-event Distribution

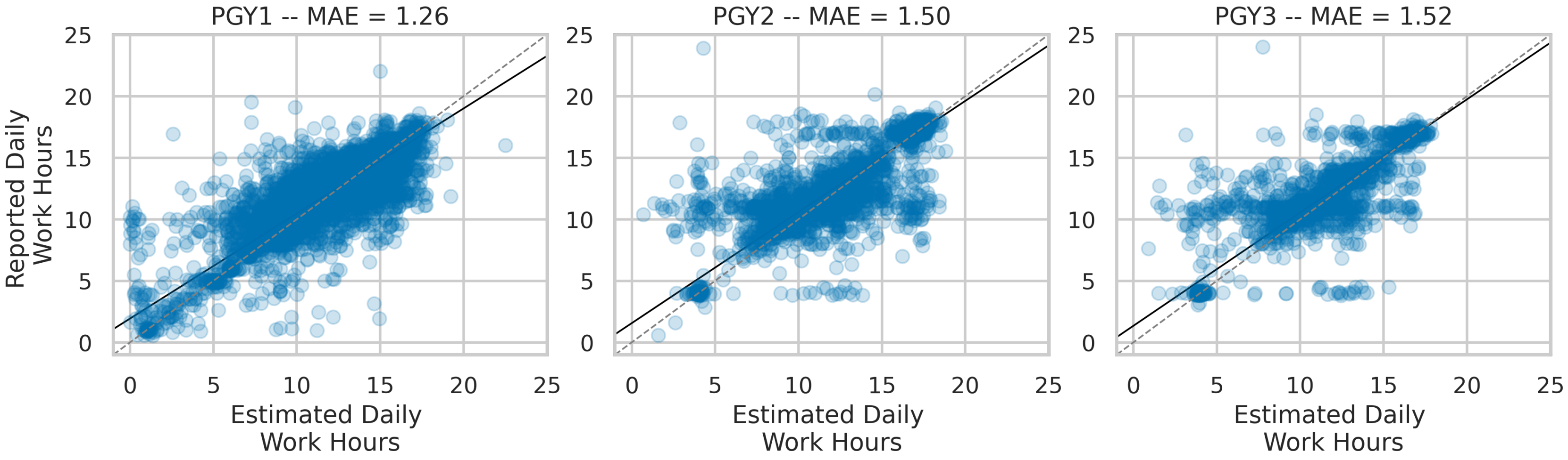


Once more than 5 hours has elapsed after a log-out, there is a 90% chance that the next log-in won't happen until at least another 5 hours, indicating the break between on-campus shifts

Retrospective Validation

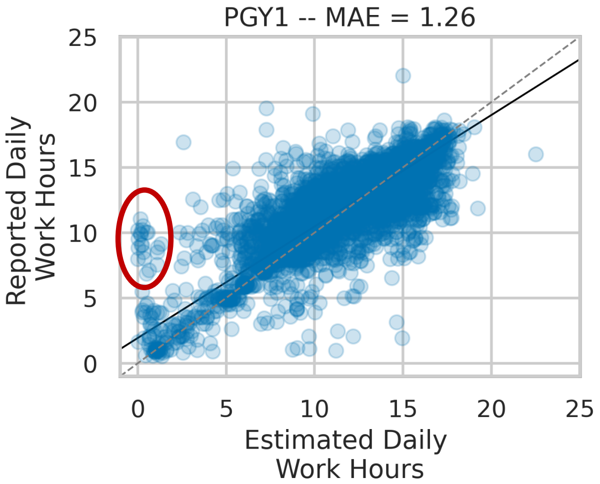
Estimated vs. Self-reported Daily Work Hours

Overall mean absolute error (MAE): 1.36 hours



Retrospective Validation

Review of Outlier Clusters

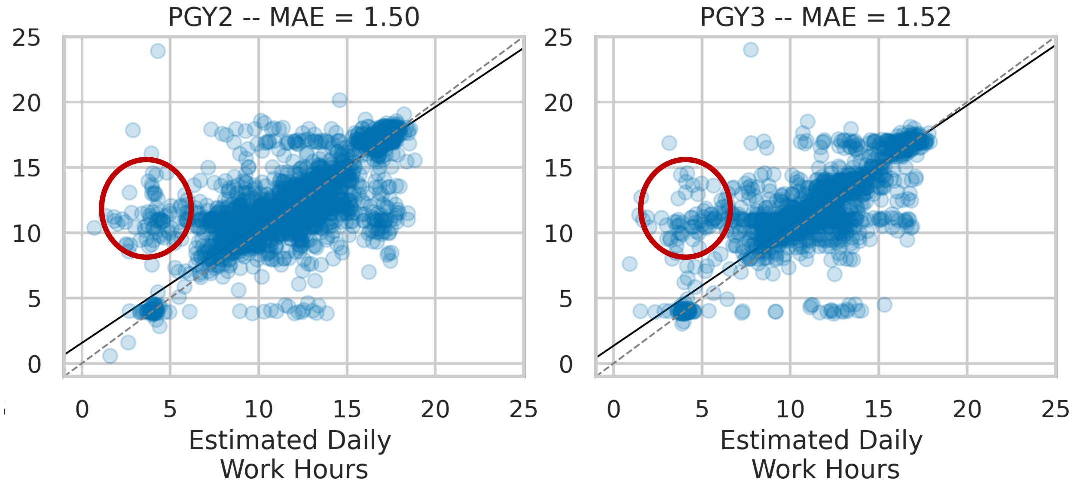


Mostly Procedures/Quality/Jeopardy rotations

Retrospective Validation

Review of Outlier Clusters

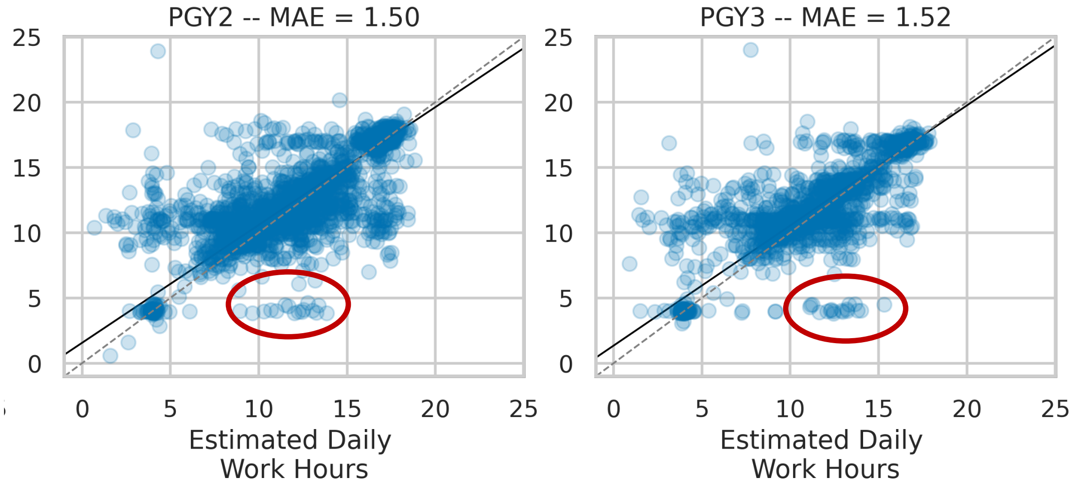
- Wrong Reporting or Wrong Schedule
    - On a UCSF rotation but may be working on other sites without updating the schedule
- Rare cases of prolonged “EHR silence” (e.g., overnight)



Retrospective Validation

Review of Outlier Clusters

- Wrong Reporting
  - They have an overnight and an evening shift (based on their schedule and EHR activity), but only report the evening hours



Model Highlights

- Retrospectively Validated
  - Against self-reported (MedHub) data from Internal Medicine residents
    - Average Absolute Error of 1.3 – 1.5 hours for PGY1 – PGY3 trainees
  - Against geolocation (ResQ) data from General Surgery residents
    - Average Absolute Error of 1.3 – 2.6 hours for PGY1 – PGY5 trainees
- Does not infringe on private trainee cell phone data
  - Only use data sources that are already being captured within the EHR as required by HIPAA (no geolocation data)

Accounting for Remote Work is Critical

- Significance:
  - In our validation study, 40-50% of 80-hour work week violations in the Internal Medicine residency program are because of remote work
  - Estimations of resident work hours need to be as inclusive as possible because ACGME annual surveys are truly capturing the perception of work hours violations
- Geolocation tools cannot identify when residents are working from home
- Our approach can distinguish remote EHR use for patient-care from checking-up on patients
  - 50-70% of remote EHR sessions include active work-related activities

Work hours shown on dashboard are only reliable on days trainees work at UCSF and ZSFG campuses.

Data last updated at [illegible]

Residency Work Hour Dashboard

(Version 1.2)

Program

[illegible]

Trainee-level Analytics

(1a) Select any row to see more details on the right (box 1b).

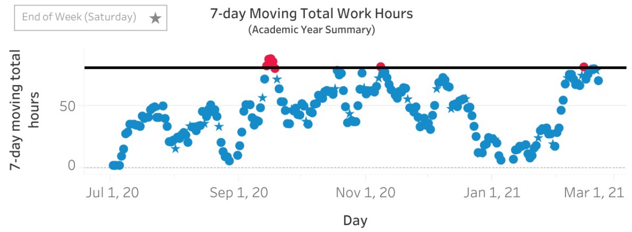
Name	Level	Rotation	Yesterday	Last 7 Days	Avg. Last 2 Weeks	Avg. Last 4 Weeks
[illegible]	[illegible]	[illegible]	3.5	70.3	75.8	61.1
[illegible]	[illegible]	[illegible]	12.8	68.0	56.7	57.2
[illegible]	[illegible]	[illegible]	3.2	66.0	76.7	66.6
[illegible]	[illegible]	[illegible]	2.1	65.9	65.9	54.5
[illegible]	[illegible]	[illegible]	10.5	64.1	62.4	55.4
[illegible]	[illegible]	[illegible]	5.9	63.0	66.1	66.5
[illegible]	[illegible]	[illegible]	14.6	59.2	67.5	65.5
[illegible]	[illegible]	[illegible]	6.0	58.0	49.0	36.2
[illegible]	[illegible]	[illegible]	9.2	57.9	57.8	50.9
[illegible]	[illegible]	[illegible]	0.0	57.1	52.1	44.2
[illegible]	[illegible]	[illegible]	5.7	56.9	62.8	65.0
[illegible]	[illegible]	[illegible]	4.9	54.6	46.3	39.1
[illegible]	[illegible]	[illegible]	0.0	54.1	54.6	43.4
[illegible]	[illegible]	[illegible]	0.0	51.6	47.6	55.4
[illegible]	[illegible]	[illegible]	0.0	48.8	56.9	54.6
[illegible]	[illegible]	[illegible]	11.1	48.3	31.0	27.2
[illegible]	[illegible]	[illegible]	0.0	45.2	41.0	46.9
[illegible]	[illegible]	[illegible]	2.6	43.5	39.8	50.6

(1b) [illegible]

Last 14 days

Select a different trainee on the left (box 1a).

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
	12.5	3.1	13.6	12.6	13.5	13.8
12.0	2.8	7.1	16.6	13.8	13.7	12.9
3.5						



Avg. Weekly Hours by Rotation
(Academic Year Summary)

Start Date	Rotation	Num Days	Avg. Weekly Total Hours
[illegible]	[illegible]	21	75.6
[illegible]	[illegible]	42	16.6
[illegible]	[illegible]	42	52.6
[illegible]	[illegible]	35	62.8
[illegible]	[illegible]	35	53.5
[illegible]	[illegible]	35	24.1
[illegible]	[illegible]	26	34.7

Method for Computing Violations: MedHub: Sun-Sat weekly hours > 80

Program-level Analytics

(2a) Data by Rotation

Rotation	Avg. Weekly Total Hours	% Trainee-Week with >80 Hour Violati..	# Trainee-Week with >80 Hour Violati..
[illegible]	[illegible]	13.0%	14
[illegible]	[illegible]	3.8%	3
[illegible]	[illegible]	1.9%	2
[illegible]	[illegible]	1.9%	1
[illegible]	[illegible]	4.2%	1
[illegible]	[illegible]	0.0%	0

(2b) Data for Rotation: All

Select a differnt rotation in box (2a)

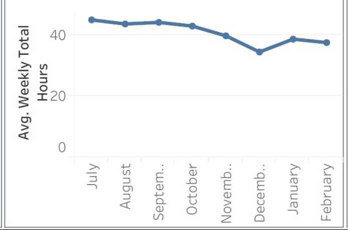
Level	Avg. Weekly Total Hours	% Trainee-Week with >80 Hour Vi..	# Trainee-Week with >80 Hour Vi..
[illegible]	44.9	1.6%	5
[illegible]	46.4	3.2%	10
[illegible]	34.6	1.2%	3
[illegible]	35.9	3.0%	9

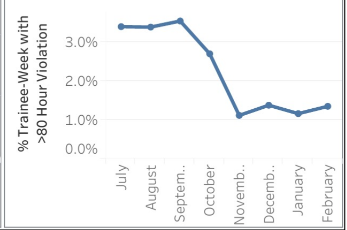
(2c) Data for Rotation: All, PGY Level: All

Select a differnt rotation in box (2a) or level in box (2b)

Trainees with Violaton

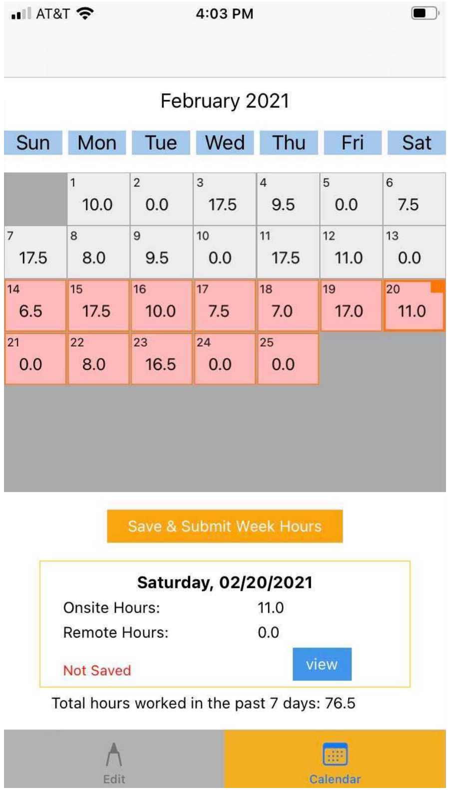
[illegible]	[illegible]	95.0
[illegible]	[illegible]	85.6
[illegible]	[illegible]	89.3
	[illegible]	101.1
	[illegible]	82.1
[illegible]	[illegible]	89.0
[illegible]	[illegible]	84.1
	[illegible]	99.0





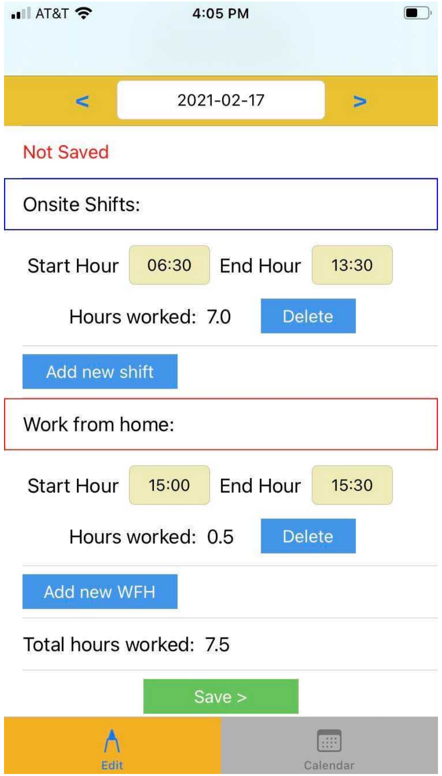
Trainee-facing Phone App

- Monthly view:
  - Summary of daily work hours over a month
  - Total hours worked in the past 7 days
  - Detailed view for each day



Trainee-facing Phone App

- Review and submit daily work hours
  - Work hours are automatically populated by the algorithm
  - Review hours, edit if needed, and submit



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- **Artificial intelligence and ethical issues**

Off-the-shelf AI

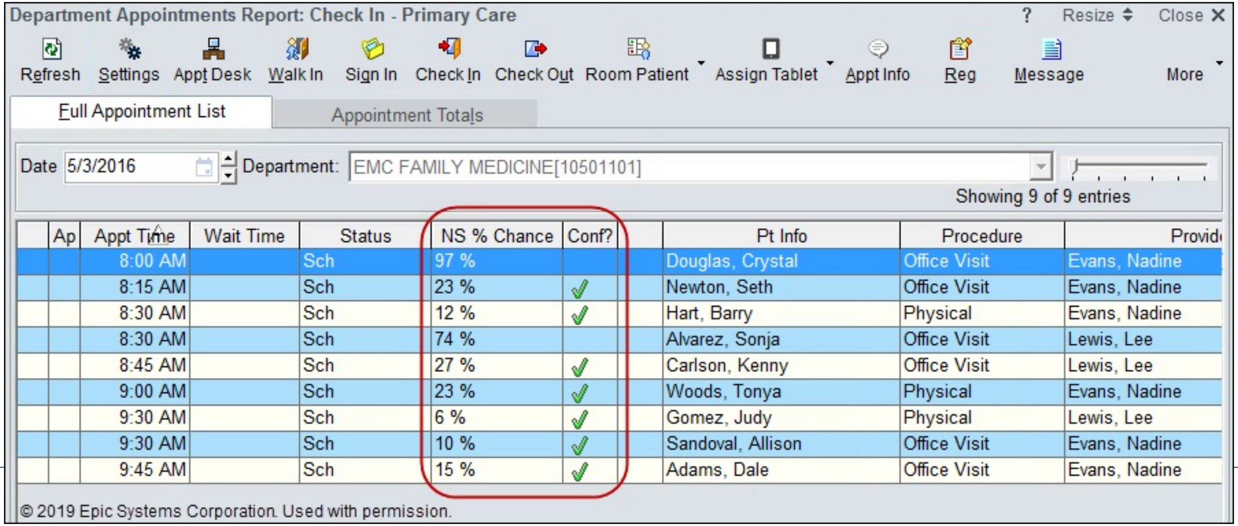
- Accurate predictive models are hard to build but even harder to implement
- Many healthcare organizations lack data science teams
- If Epic builds it into the EHR, everyone could use it

What is Trustworthy AI? **Lawful, Ethical, Robust**

7 requirements outlined by EU
Human agency and oversight
Technical robustness and safety
Privacy and data governance
Transparency
Diversity, non-discrimination, and fairness
Societal and environmental well-being
Accountability

Predicting Clinic No-Shows

- Patients no-show to clinic appointments 2.6-16.1% of the time
  - 267,000 lost appointment slots annually, revenue impact >$100million
- Epic provides a model that includes 22 variables



Ap	Appt Time	Wait Time	Status	NS % Chance	Conf?	Pt Info	Procedure	Provid
	8:00 AM		Sch	97 %		Douglas, Crystal	Office Visit	Evans, Nadine
	8:15 AM		Sch	23 %	✓	Newton, Seth	Office Visit	Evans, Nadine
	8:30 AM		Sch	12 %	✓	Hart, Barry	Physical	Evans, Nadine
	8:30 AM		Sch	74 %		Alvarez, Sonja	Office Visit	Lewis, Lee
	8:45 AM		Sch	27 %	✓	Carlson, Kenny	Office Visit	Lewis, Lee
	9:00 AM		Sch	23 %	✓	Woods, Tonya	Physical	Evans, Nadine
	9:30 AM		Sch	6 %	✓	Gomez, Judy	Physical	Lewis, Lee
	9:30 AM		Sch	10 %	✓	Sandoval, Allison	Office Visit	Evans, Nadine
	9:45 AM		Sch	15 %	✓	Adams, Dale	Office Visit	Evans, Nadine

Predicting Clinic No-Shows

Make overbooking more effective?

Clinic Overbooking to Improve Patient Access and Increase Provider Productivity*

Linda R. LaGanga†
Director of Quality Systems, Mental Health Center of Denver, 4141 East Dickenson Place, Denver, CO 80222, e-mail: linda.laganga@colorado.edu

Stephen R. Lawrence
Leeds School of Business, University of Colorado at Boulder, 419 UCB, Boulder, CO 80309-0419, e-mail: stephen.lawrence@colorado.edu

Tired of "no-show" patients? Use predictive overbooking.

3:20 PM on January 10, 2017 by **Gunjan Desai**

see related editorial on page 1274

Preventing Endoscopy Clinic No-Shows: Prospective Validation of a Predictive Overbooking Model

Mark W. Reid, PhD[1,2], Folasade P. May, MD, MPhil[1,3], Bibiana Martinez, MPH[2], Samuel Cohen, MD[1], Hank Wang, MD, MSHS[4], Demetrius L. Williams Jr, MPA[1,2] and Brennan M.R. Spiegel, MD, MSHS[1,2,5,6]

Research Article   aci Applied Clinical Informatics   836

Patient No-Show Predictive Model Development using Multiple Data Sources for an Effective Overbooking Approach

Y. Huang[1]; D.A. Hanauer[2]

[1]New Mexico State University, Industrial Engineering, Las Cruces, New Mexico, United States; [2]Department of Pediatrics, University of Michigan Medical School, Ann Arbor, MI

Predicting Clinic No-Shows

Patient Age
Language
Sex
Last BMI
Adopted

Feature
No-Show Count for Previous Two Appointments
Average Lead Time
Confirmation Status
Appointment Day of Week
Appointment Changed
Appointment Rescheduled

Predicting Clinic No-Shows

Patient Age
Language
Sex
Last BMI
Adopted

Feature
No-Show Count for Previous Two Appointments
Average Lead Time
Confirmation Status
Appointment Day of Week
Appointment Changed
Appointment Rescheduled

Predicting Clinic No-Shows

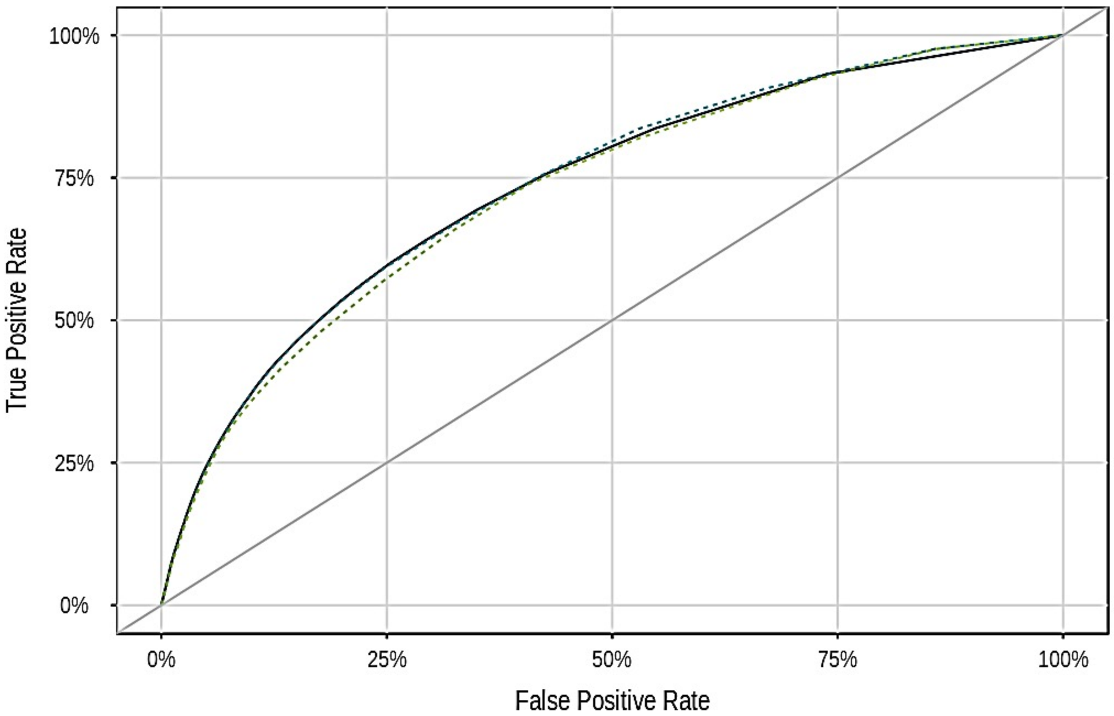
Patient Age
Language
Sex
Last BMI
Adopted

Feature
No-Show Count for Previous Two Appointments
Average Lead Time
Confirmation Status
Appointment Day of Week
Appointment Changed
Appointment Rescheduled

Predicting Clinic No-Shows

- So we rebuilt the model with some reclassification of features and excluding sensitive characteristics…

Model	Area Under Curve ("AUC", 1.0 = perfect predictor)
UCSF Not-Protected w/o Financial Class	0.728
Epic standard	0.722

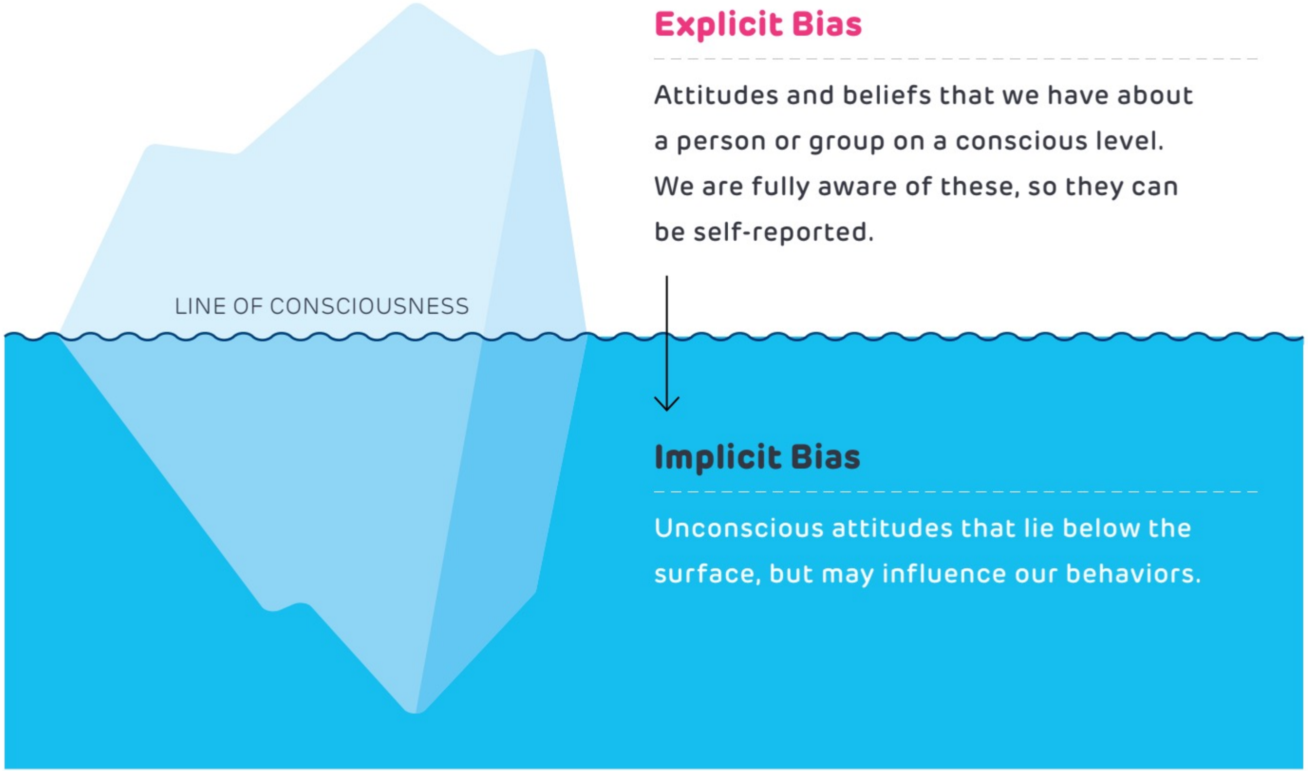


Artificial Intelligence and Automated Discrimination

Explicit Bias vs. Implicit Bias

UCSF

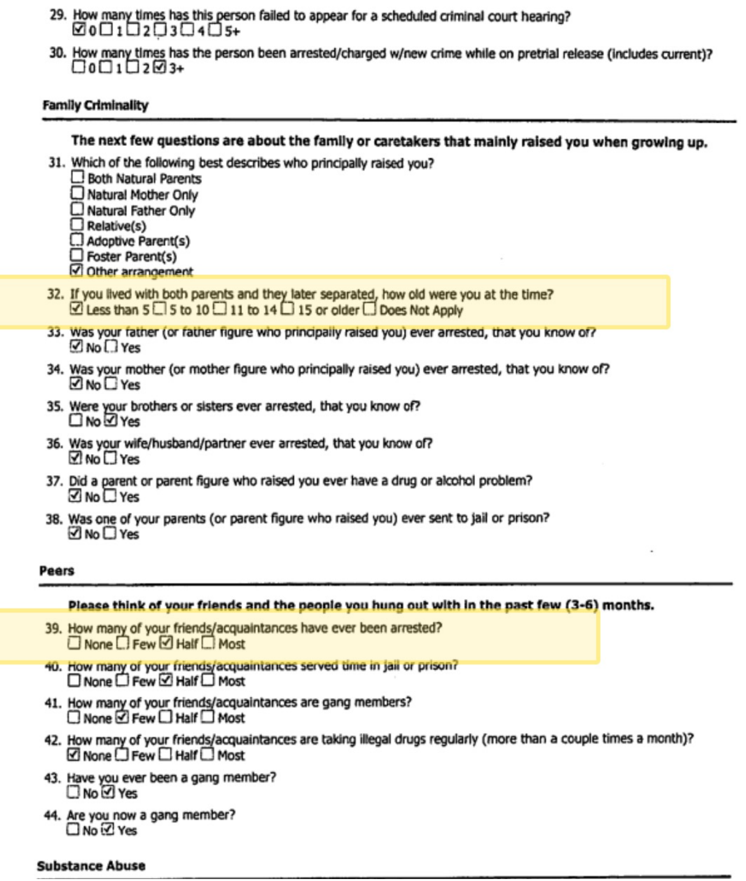
Artificial Intelligence and Automated Discrimination



Artificial Intelligence and Automated Discrimination

COMPAS and criminal justice

- Widely used proprietary algorithm to predict criminal recidivism
  - incorporating 137 survey questions
  - <u>Never asks race</u>
  - Used by judges in sentencing



29. How many times has this person failed to appear for a scheduled criminal court hearing?
☑ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+

30. How many times has the person been arrested/charged w/new crime while on pretrial release (includes current)?
☐ 0 ☐ 1 ☐ 2 ☑ 3+

Family Criminality

The next few questions are about the family or caretakers that mainly raised you when growing up.

31. Which of the following best describes who principally raised you?
☐ Both Natural Parents
☐ Natural Mother Only
☐ Natural Father Only
☐ Relative(s)
☐ Adoptive Parent(s)
☐ Foster Parent(s)
☑ Other arrangement

32. If you lived with both parents and they later separated, how old were you at the time?
☑ Less than 5 ☐ 5 to 10 ☐ 11 to 14 ☐ 15 or older ☐ Does Not Apply

33. Was your father (or father figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

34. Was your mother (or mother figure who principally raised you) ever arrested, that you know of?
☑ No ☐ Yes

35. Were your brothers or sisters ever arrested, that you know of?
☐ No ☑ Yes

36. Was your wife/husband/partner ever arrested, that you know of?
☑ No ☐ Yes

37. Did a parent or parent figure who raised you ever have a drug or alcohol problem?
☑ No ☐ Yes

38. Was one of your parents (or parent figure who raised you) ever sent to jail or prison?
☑ No ☐ Yes

Peers

Please think of your friends and the people you hung out with in the past few (3-6) months.

39. How many of your friends/acquaintances have ever been arrested?
☐ None ☐ Few ☑ Half ☐ Most

40. How many of your friends/acquaintances served time in jail or prison?
☐ None ☐ Few ☑ Half ☐ Most

41. How many of your friends/acquaintances are gang members?
☐ None ☑ Few ☐ Half ☐ Most

42. How many of your friends/acquaintances are taking illegal drugs regularly (more than a couple times a month)?
☑ None ☐ Few ☐ Half ☐ Most

43. Have you ever been a gang member?
☐ No ☑ Yes

44. Are you now a gang member?
☐ No ☑ Yes

Substance Abuse

Artificial Intelligence and Automated Discrimination

COMPAS and criminal justice

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

Predicting Clinic No-Shows – human intelligence matters

Interventions

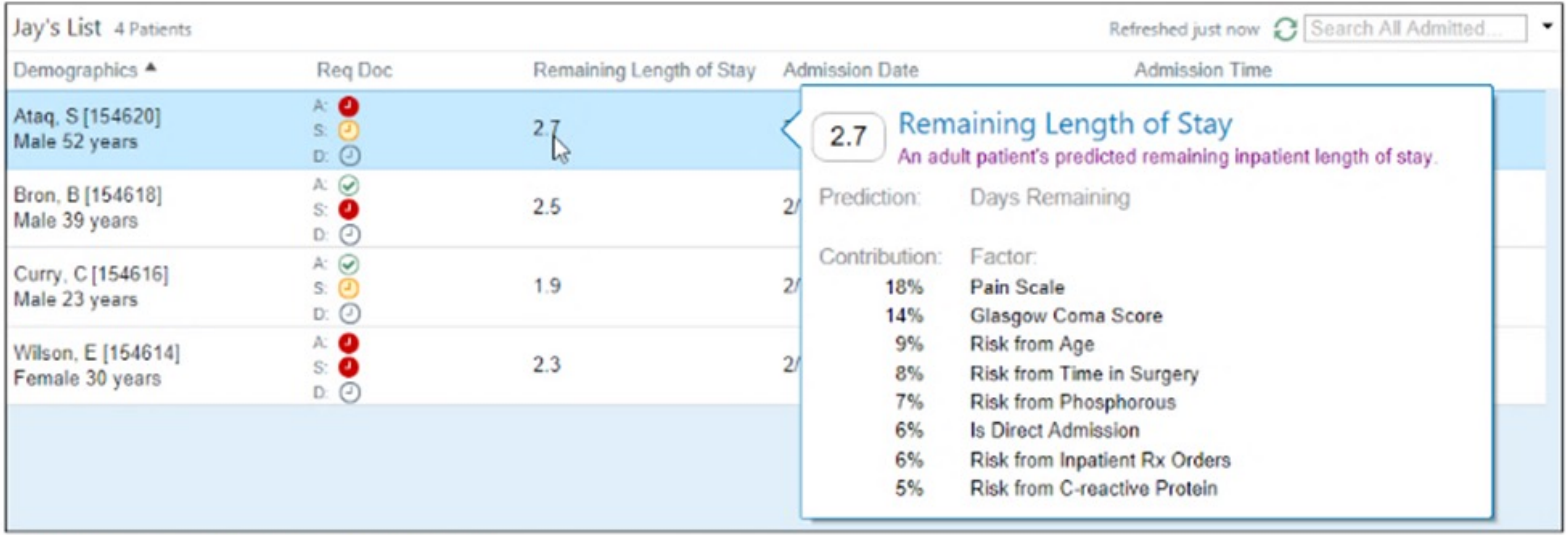
Patient Positive: **reminders, outreach, Lyft**

~~*Patient Negative*: overbooking~~

3 month pilot in 12 departments →
avoided 299 no-shows

https://www.healthaffairs.org/do/10.1377/hblog20200128.626576/full/

Predicting Length of Stay



R-squared = 0.09

Predicting Length of Stay

Double dice roll outperformed Epic's AI model by 17% in patients with LOS<7d (21% true prediction vs. 18% for the AI model)

Generalizability

Netflix and their million-dollar algorithm

Take home points

- Think about data and potential for confounding and bias
- There are infinite opportunities for using EHR data and data science to change how we deliver healthcare
- Artificial intelligence demonstrates promise for cohort identification and predicting outcomes
    - Must evaluate for trustworthiness

Questions?