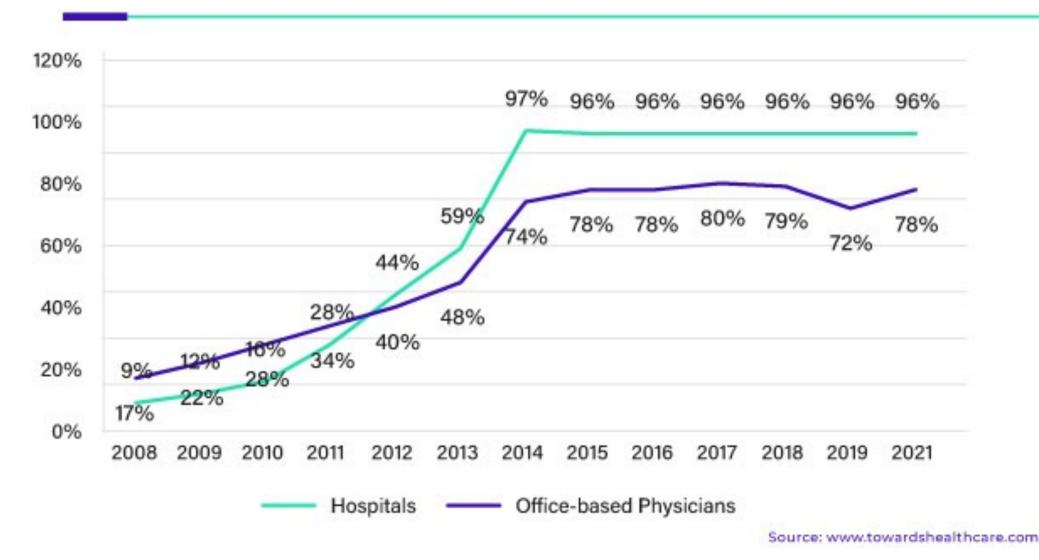


Data 146: Foundations for CPH Electronic Health Records

Irene Y. Chen



Trend in U.S. Hospitals and Physician EHR Adoption



Outline

- EHR Adoption (30 mins)
- MIMIC Deep Dive (20 mins)



How can we make Data 146 better for you?

Learning Objective: Understand how EHR data came to be and potential issues

Why did hospitals adopt the electronic health record?



HITECH Act of 2009

HITECH Act

- Health Information Technology for Economic and Clinical Health (HITECH) ACT of 2009
- Of \$840 billion stimulus package in 2009, \$30 billion was allotted for hospitals and medical providers for "meaningful use" of certified EHR systems
 - Payments linked to improvements in quality, safety, and efficiency



How would you allocate \$30 billion? (Partner discussion)

Health IT Policy Committee

- Created under the HITECH Act as an advisory committee
- Recommend policies and defined "meaningful use" of EHRs
- Included federal appointees, representatives from healthcare, technology, academia, and patient advocates
- Included Judy Faulkner, CEO of Epic



Judy Faulkner

Founder & CEO, Epic Systems

\$7.8B

Real Time Net Worth as of 10/28/25

#469 in the world today

\$7.8B

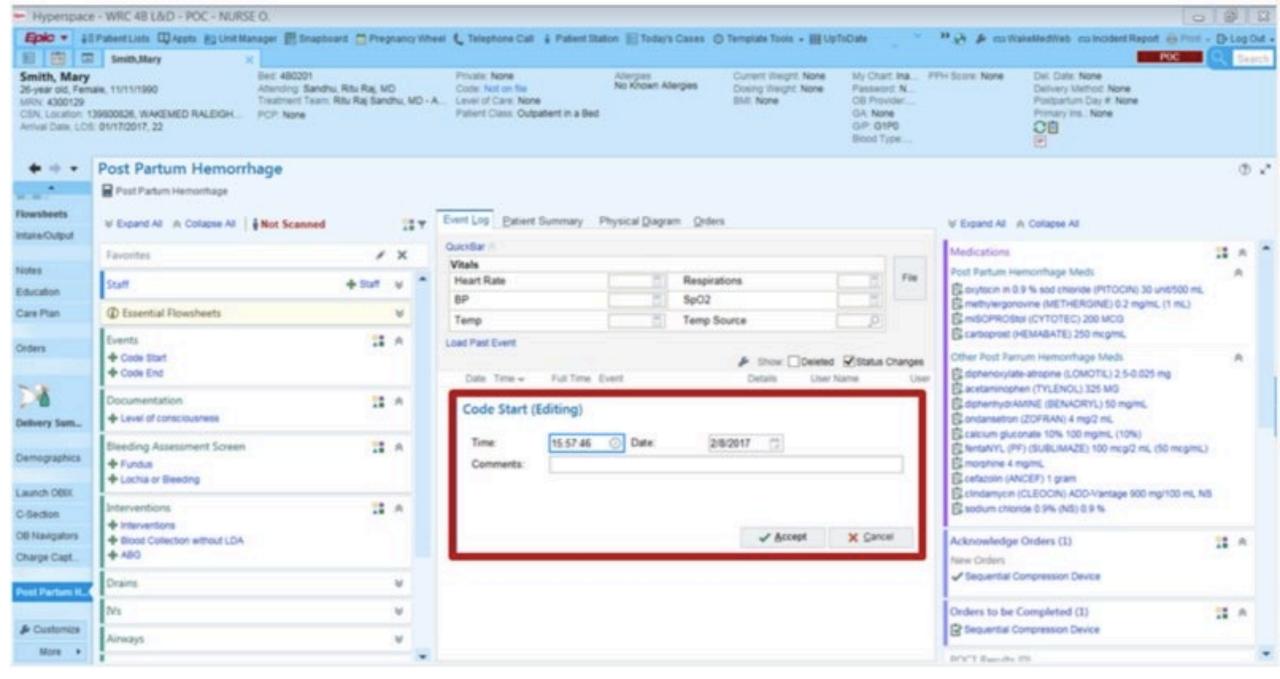
2025 America's Richest Self-Made Women Net Worth

as of 6/3/25









What is "meaningful use"?

- Data capture and sharing
- Hospital had to demonstrate basic capabilities about data entry and clinical quality measures
- Record demographics, problem lists, medications, lab results, electronic prescribing

What is missing here? (Partner discussion)

Problems with original recommendations

- Limited data exchange: No need to share data or facilitate exchange with patients or other hospitals
- Vendor lock-in: Each EHR vendor has its own data format. No crossvendor interoperability means vendors are incentivized to silo in hospitals and have high switching costs
- Improved clinical outcomes: More documentation could slow down clinical workflows. How do you incentivize structures that actually improve clinical care?
- Patient rights: Hospitals control all of the data and nothing is written with the patient in mind.

PERSPECTIVE

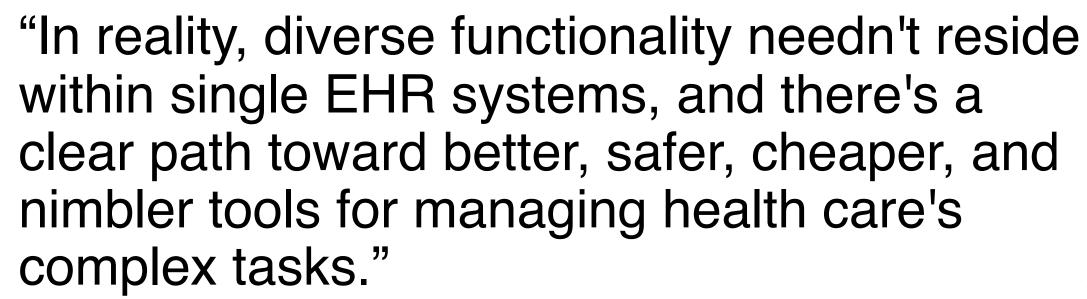


Escaping the EHR Trap — The Future of Health IT

Authors: Kenneth D. Mandl, M.D., M.P.H., and Isaac S. Kohane, M.D., Ph.D. Author Info & Affiliations

Published June 14, 2012 | N Engl J Med 2012;366:2240-2242 | DOI: 10.1056/NEJMp1203102

VOL. 366 NO. 24 | Copyright © 2012



21st Century Cures Act

- Merged and replaced previous committees with one that focuses on interoperability, privacy, and patient empowerment
- Explicitly prohibited "information blocking", meaning EHR vendors or health systems that prevent data sharing
- Required development for standardized APIs (like FHIR) to allow patients and third party apps to securely access and exchanged health data

In 2015, lots of open EHR datasets

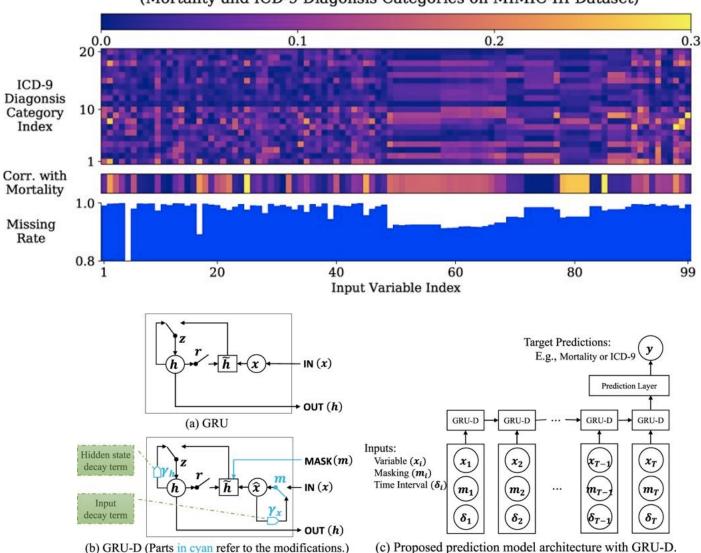
- MIMIC-IV: 65k patients intensive care unit (ICU) and emergency department (ED) data from Beth Israel Deaconess Medical Center in Boston
- All of Us research program: 200k patients including EHR, genomics, wearables, and patient surveys in standardized (OMOP) format from NIH
- EHRSHOT: 6k patients and 900k visits from Stanford

What is MIMIC?

- Largest open dataset for clinical healthcare (for authorized researchers)
- Dataset of 26 tables (e.g. admissions, patients)
- Maintained by Roger Mark's lab at MIT
- OPotential place for final project ideas!

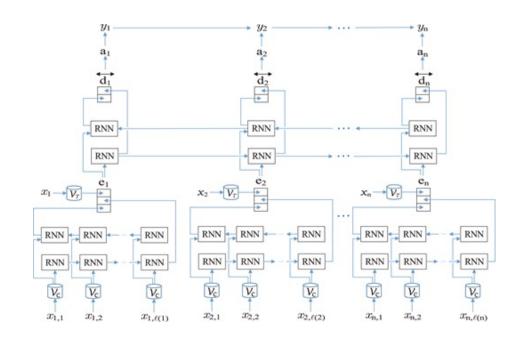
Recurrent Neural Networks for Multivariate Time Series with Missing Values

Che et al, 2018 (Nature Scientific Reports) Absolute Values of Pearson Correlations between Variable Missing Rates and Labels (Mortality and ICD-9 Diagonsis Categories on MIMIC-III Dataset)



De-identification of patient notes with recurrent neural network

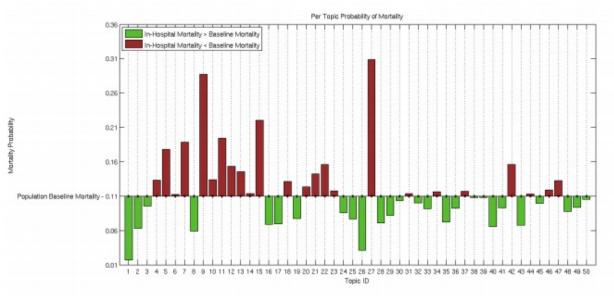
Dernoncourt et al, 2017 (JAMIA)



	i2b2			МІМІС		
Model	Precision	Recall	F1	Precision	Recall	F1
Nottingham	99.000	96.400	97.680	-	-	-
MIST	91.445	92.745	92.090	95.867	98.346	97.091
CRF	98.560	96.528	97.533	99.060	98.987	99.023
ANN	98.320	97.380	97.848	99.208	99.251	99.229
CRF + ANN	97.920	<u>97.835</u>	<u>97.877</u>	98.820	99.398	99.108

Unfolding Physiological State: Mortality Modeling in Intensive Care Units

Ghassemi et al, 2014 (KDD)

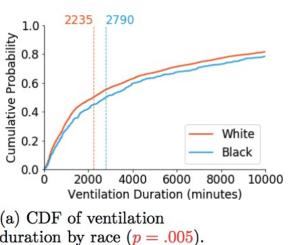


	Topi	c Top Ten Words	Possible Topic				
In-	27	name, family, neuro, care,	Discussion				
hospital		noted, status, plan, stitle,	of end-				
Mor-		dr, remains	of-life				
tality			care				
	15	intubated, vent, ett, secre-	Respiratory				
		tions, propofol, abg, respi-	failure				
		ratory, resp, care, sedated					
	7	thick, secretions, vent,	Respiratory				
		trach, resp, tf, tube,	infection				
		coarse, cont, suctioned					
	5	liver, renal, hepatic,	Renal				
		ascites, dialysis, failure,	Failure				
		flow, transplant, portal,					
		ultrasound					

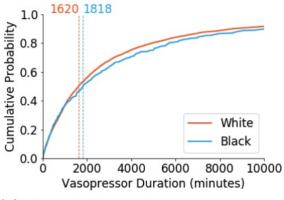
Racial Disparities and Mistrust in Endof-Life Care

Social: Pt refused to sign ICU consent and expressed wishes to be DNR/DNI, seemingly very frustrated and mistrusting of healthcare system in relation to Also, w/ hx of poor medication compliance and follow-up

Boag et al, 2018 (MLHC)



(a) CDF of ventilation duration by race (p = .005).



(b) CDF of vasopressor duration by race (p = 0.12).

Reproducibility in critical care: a mortality prediction case study

Johnson et al, 2017 (MLHC)

We reproduced datasets for 38 experiments corresponding to 28 published studies using MIMIC. In half of the experiments, the sample size we acquired was 25% greater or smaller than the sample size reported. The highest discrepancy was 11,767 patients. While accurate reproduction of each study cannot be guaranteed, we believe that these results highlight the need for more consistent reporting of model design and methodology to allow performance improvements to be compared. We discuss the challenges in reproducing the cohorts used in the studies, highlighting the importance of clearly reported methods (e.g. data cleansing, variable selection, cohort selection) and the need for open code and publicly available benchmarks.

| Window | Inclusion suitorio

C+-- ---

Study	Window,	Inclusion criteria	
	W (hours)		
Caballero Barajas and	24	Age>18, Random fixed size subsample	
Akella (2015)			
Caballero Barajas and	48	Age>18, Random fixed size subsample	
Akella (2015)			
Caballero Barajas and	72	Age>18, Random fixed size subsample	
Akella (2015)			
Calvert et al. (2016b)	5*	Age>18, In MICU, >1 obs. for all fea-	
		tures, LOS ≥ 17hr, ICD-9 codes indicat-	
		ing alcohol withdrawal	
Calvert et al. (2016a)	5*	Age>18, In MICU, >1 obs. for all fea-	
		tures, $500hr \ge LOS \ge 17hr$	
Celi et al. (2012)	72	ICD-9 code 584.9	
Celi et al. (2012)	24	ICD-9 code 430 or 852	
Che et al. (2016) (b)	48	PhysioNet 2012 Challenge dataset	
Ding et al. (2016)	48	PhysioNet 2012 Challenge dataset	
Ghassemi et al. (2014)	12	Age>18, >100 words across all notes	
Ghassemi et al. (2014)	24	Age>18, >100 words across all notes	
Ghassemi et al. (2015)	24	Age>18, >100 words across all notes, >6	
		notes	

EHR Safari: Data is Contextual

William Boag

WBOAG@MIT.EDU

MIT CSAIL Cambride, MA, USA

MOLADIPO@MIT.EDU

Mercy Oladipo

MIT CSAIL
Cambride, MA, USA

PSZ@MIT.EDU

Peter Szolovits

MIT CSAIL Cambride, MA, USA

"we demonstrate numerous examples where a non-clinician's intuition may lead to incorrect — and potentially harmful — modeling assumptions"

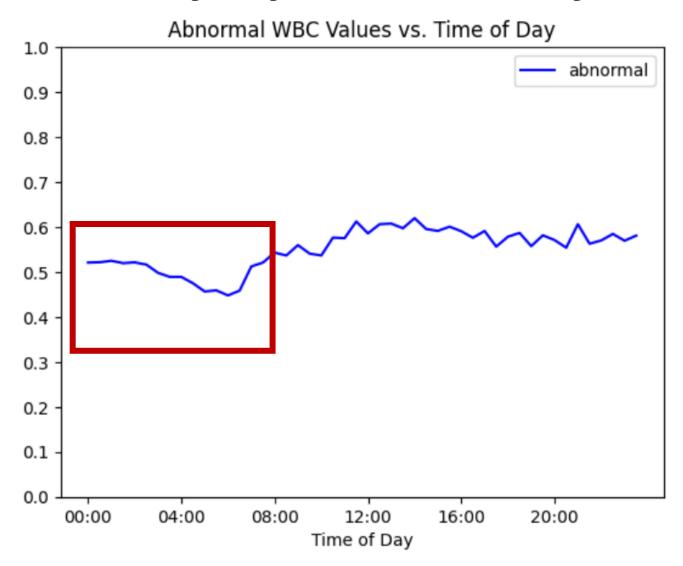
Problems with MIMIC

- 1. Inconsistent timestamps
- 2. Lab values vary by time of day
- 3. Multiple copies of provider notes
- 4. Missing death date collection

Inconsistent time stamps

- We want time stamps that show:
 - hospital admission time (admittime) ≤
 - patient enters ICU (intime) ≤
 - patient leaves ICU (outtime) ≤
 - patient discharged from hospital (dischtime)
- BUT, of 57k ICU stays, this ordering only holds 79% of the time
 - Because hospital and ICU staff have their own paperwork, things can get filed out of sync

Lab values vary by time of day

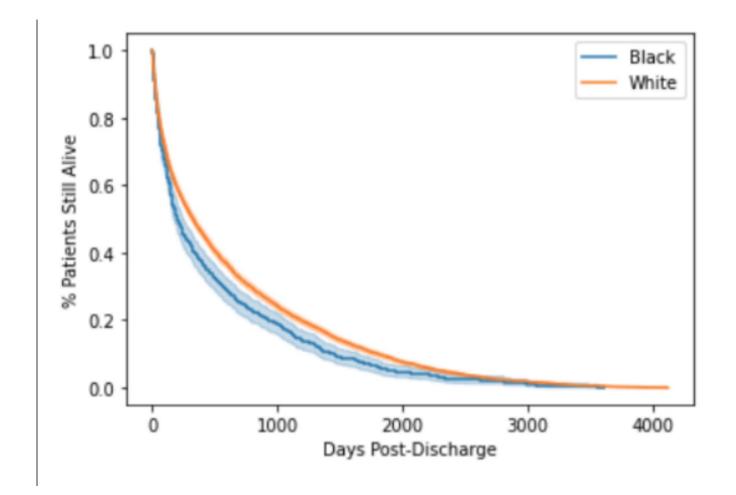


Multiple copies of provider notes

- NLP techniques use clinical notes to predict clinical outcomes
- MIMIC contains all note drafts that EHR autosaves
 - Disconnect between the chart time (completed) and the store time (partially written)

Missing death date collection

- Higher rate of mortality for white patients than black patients??
- Because 2013
 legislative change forbid SSN collection from state records, this led to 40% change in capture of death information



More reading

 Caldwell, "We've Spent Billions to Fix Our Medical Records and They're Still a Mess", November 2015

 Boag et al, "EHR Safari: Data is Contextual", MLHC 2022.

Mother Jones

Smart, Fearless Journalism

Donate

FOOD

PODCAST

MAGAZINE

We've Spent Billions to Fix Our Medical Records, and They're Still a Mess. Here's Why.

Digitizing America's medical records was supposed to help patients and save money. Why hasn't that happened?

PATRICK CALDWELL NOVEMBER/DECEMBER 2015 ISSUE











EHR Safari: Data is Contextual

William Boag MIT CSAIL

Cambride, MA, USA

Mercy Oladipo

MIT CSAIL

Cambride, MA, USA

Peter Szolovits

MIT CSAIL

Cambride, MA, USA

WBOAG@MIT.EDU

MOLADIPO@MIT.EDU

PSZ@MIT.EDU

Summary

- ✓ Creation of the modern EHR (30 mins)
- ✓ Deep dive into MIMIC (20 mins)



How can we make Data 146 better for you?

Next Class: Other health datasets and where to find them