The Path Forward for AI in Healthcare

Bridging Technology and Nursing Gaps

Northwestern

AI@NU

AI@NU is a community of researchers, educators, and students across Northwestern advancing artificial intelligence in theory and practice.

Through interdisciplinary collaborations and innovative AI endeavors within many fields, we advance ethical, visionary research and pedagogy that empowers individuals, organizations, and society.

We stimulate conversation, foster connections, and cultivate opportunities to develop and evolve Northwestern as a local, national, and international hub for AI expertise.

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Institute for Augmented Intelligence in Medicine

The mission of the Institute for Augmented Intelligence in Medicine is to bridge computational methods with human expertise to advance medical science and improve human health.

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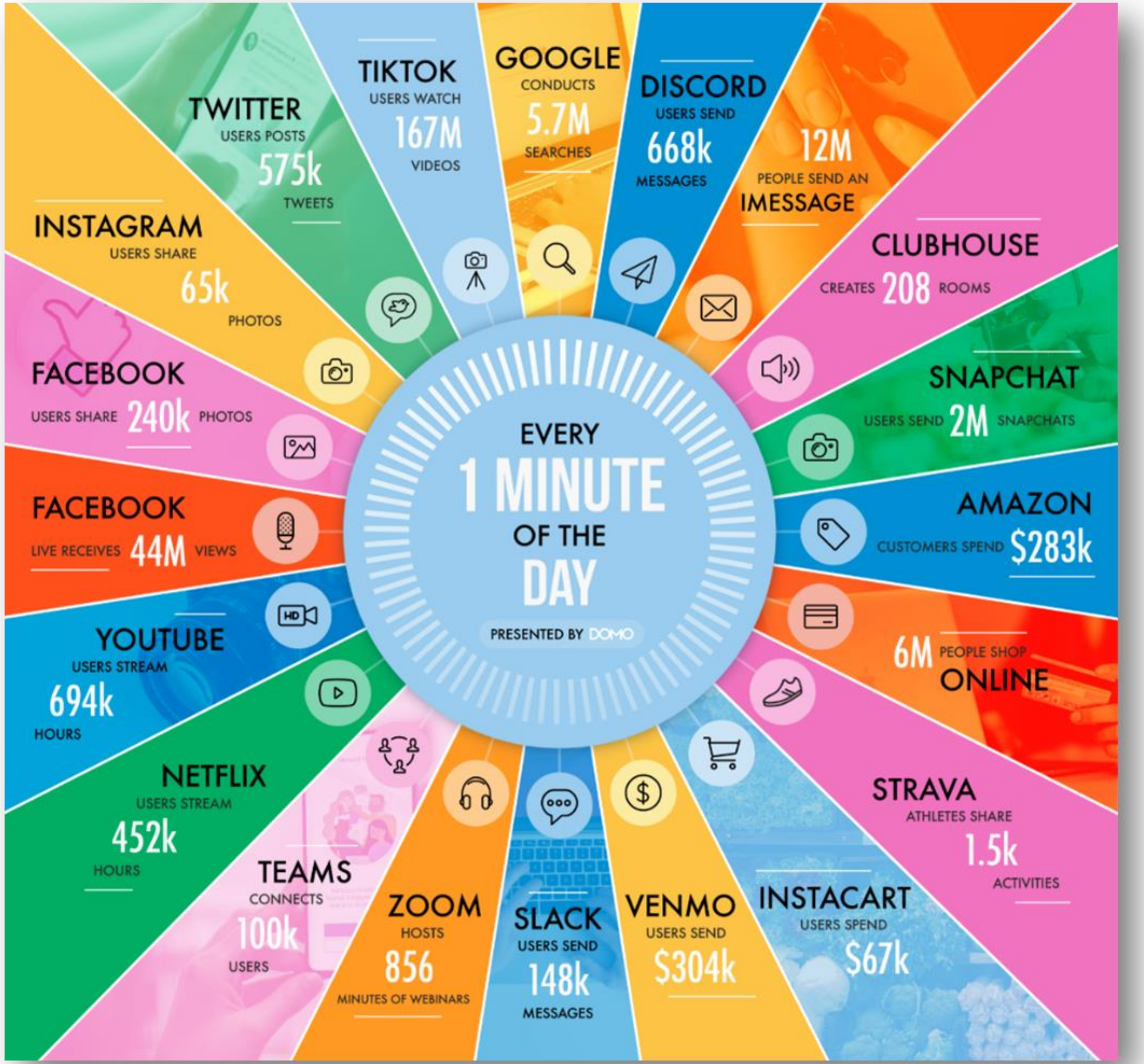
Data is ubiquitous and we are surrounded every day by AI driven algorithms



The Rise of the Machine

Who Knew Healthcare Was So Complicated?

Global Edition Artificial Intelligence

IBM to sell Watson Health assets to Francisco Partners

The deal with the private equity firm is a "clear next step as IBM becomes even more focused on our platform-based hybrid cloud and AI strategy," said a Big Blue exec.

By Mike Miliard | January 21, 2022 | 10:24 AM

Photo: HIMSS

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MEDTECH

Google reorganizes health division, shedding 130 employees and dropping consumer health focus: report

By Andrea Park · Jun 18, 2021 09:35am

Haven, the Amazon-Berkshire-JPMorgan venture to disrupt health care, is disbanding after 3 years

PUBLISHED MON, JAN 4 2021•12:21 PM EST | UPDATED TUE, JAN 5 2021•11:56 AM EST

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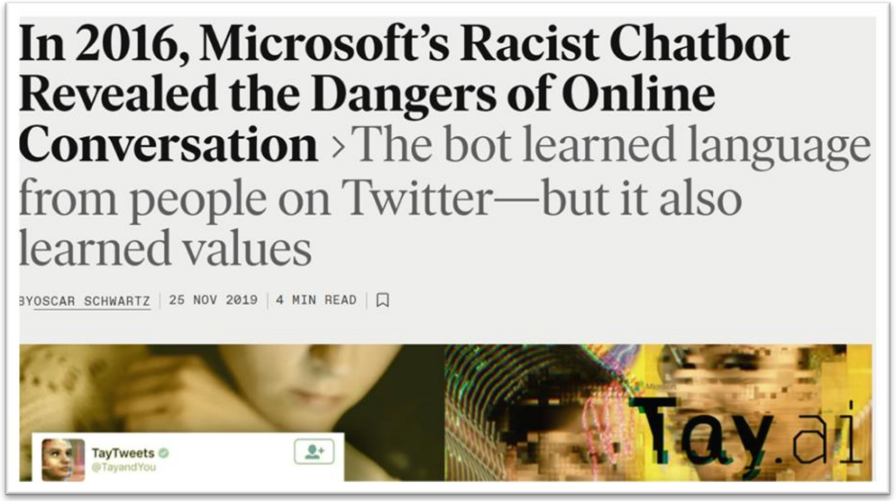
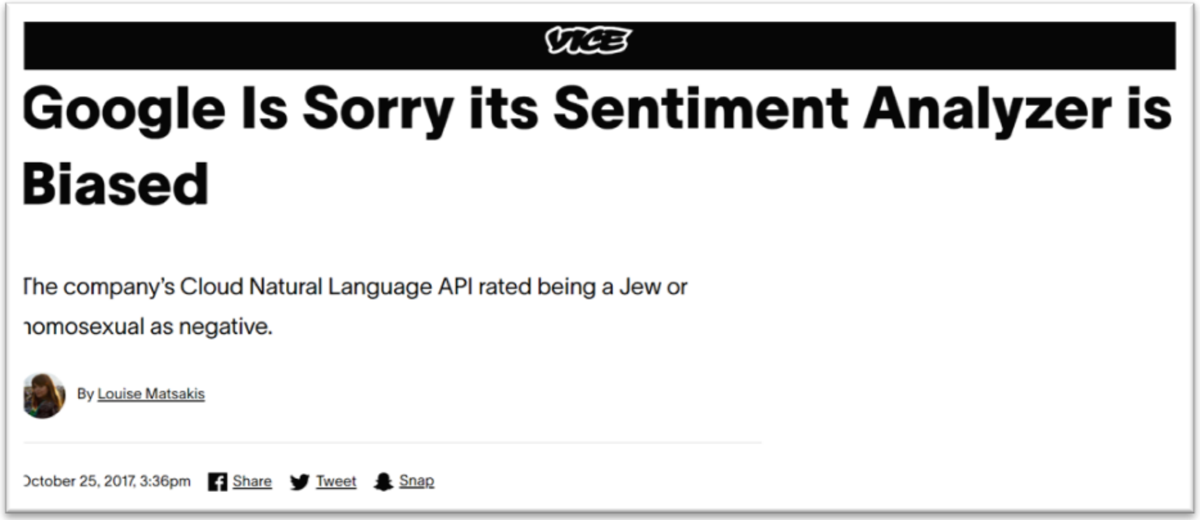
Who Knew Machines Could Be Biased?


In 2016, Microsoft's Racist Chatbot Revealed the Dangers of Online Conversation › The bot learned language from people on Twitter—but it also learned values

BYOSCAR SCHWARTZ | 25 NOV 2019 | 4 MIN READ

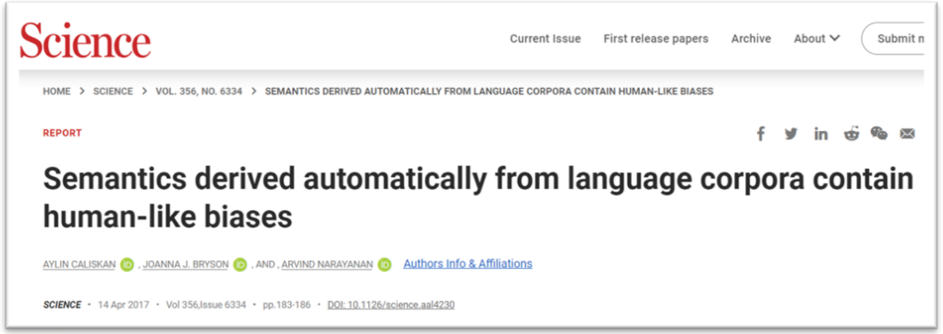


Google Is Sorry its Sentiment Analyzer is Biased

The company's Cloud Natural Language API rated being a Jew or homosexual as negative.

By Louise Matsakis

October 25, 2017, 3:36pm Share Tweet Snap



HOME › SCIENCE › VOL. 356, NO. 6334 › SEMANTICS DERIVED AUTOMATICALLY FROM LANGUAGE CORPORA CONTAIN HUMAN-LIKE BIASES

REPORT

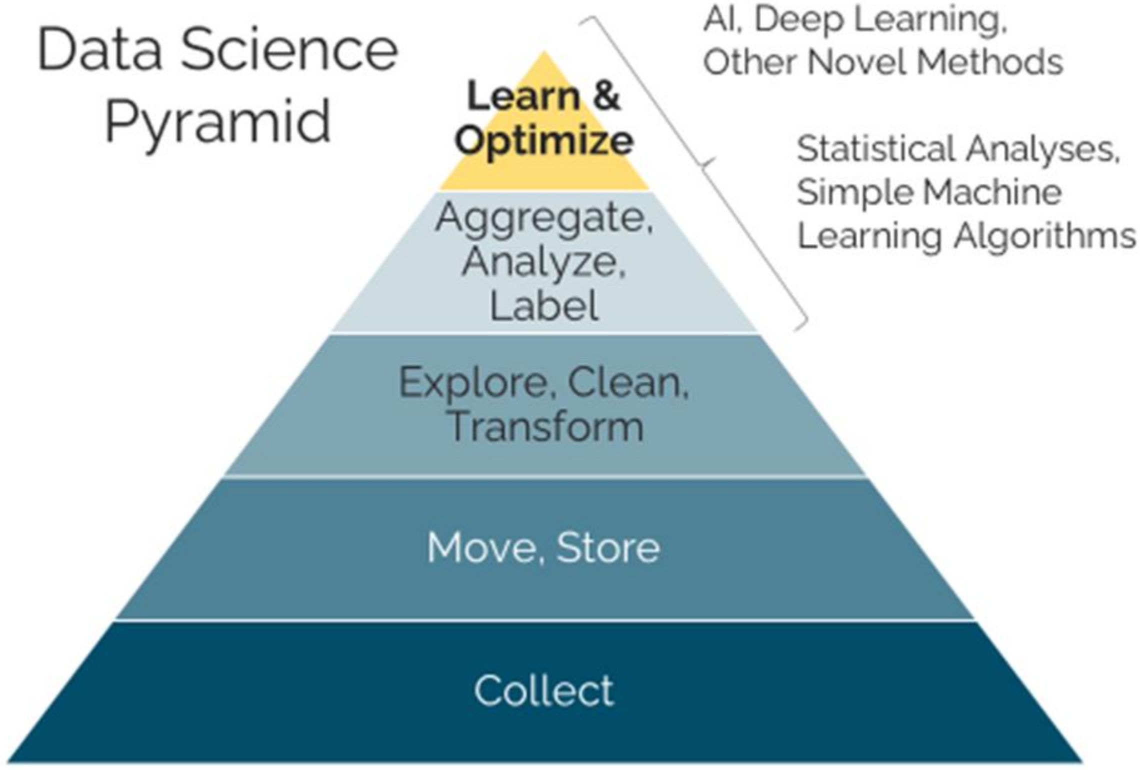
Semantics derived automatically from language corpora contain human-like biases

AYLIN CALISKAN, JOANNA J. BRYSON, AND ARVIND NARAYANAN Authors Info & Affiliations

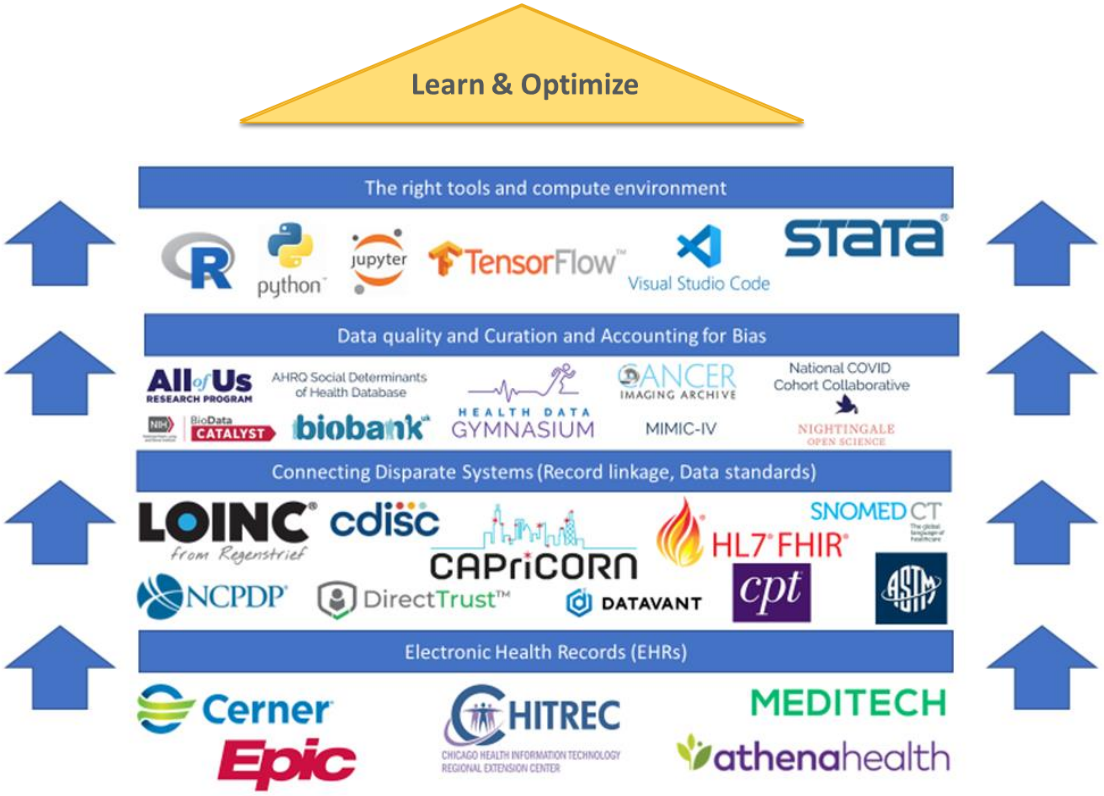
SCIENCE • 14 Apr 2017 • Vol 356,Issue 6334 • pp.183-186 • DOI: 10.1126/science.aal4230

"We are suggesting that instead of trying to remove bias from the machine, [we should] put a human in the loop to help the machine make the right decision." - Aylin Caliskan, Princeton University's Center for Information Technology Policy.

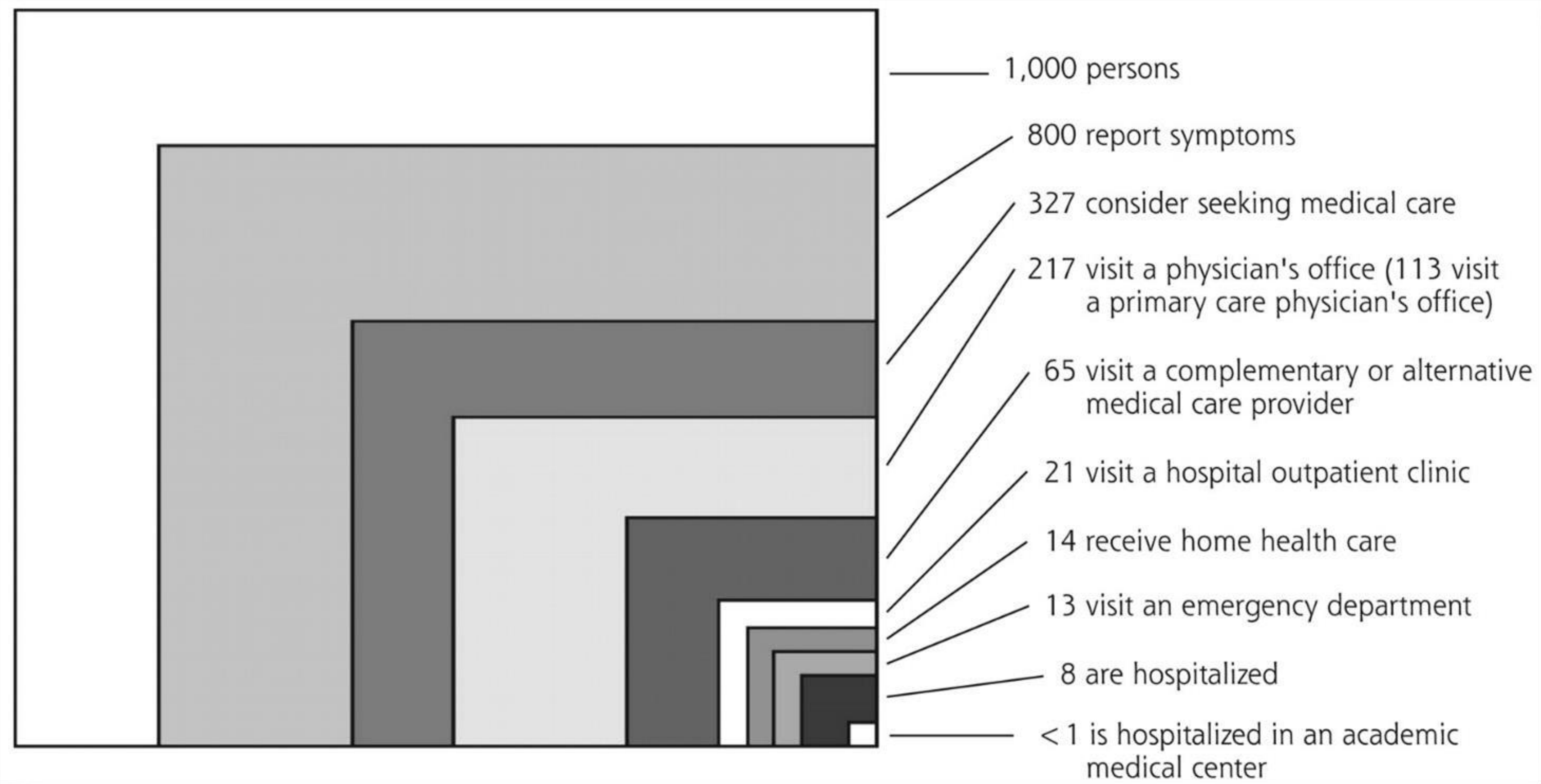
Why AI in Healthcare is so Hard?



Adapted from: M. Rogati. (2017). The AI hierarchy of needs. *HackerNoon*
https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007



Data Collection is Limited



Green et al, The Ecology of Medical Care Revisited. NEJM 2001

Geographic Distribution of US Cohorts Used to Train Deep Learning Algorithms

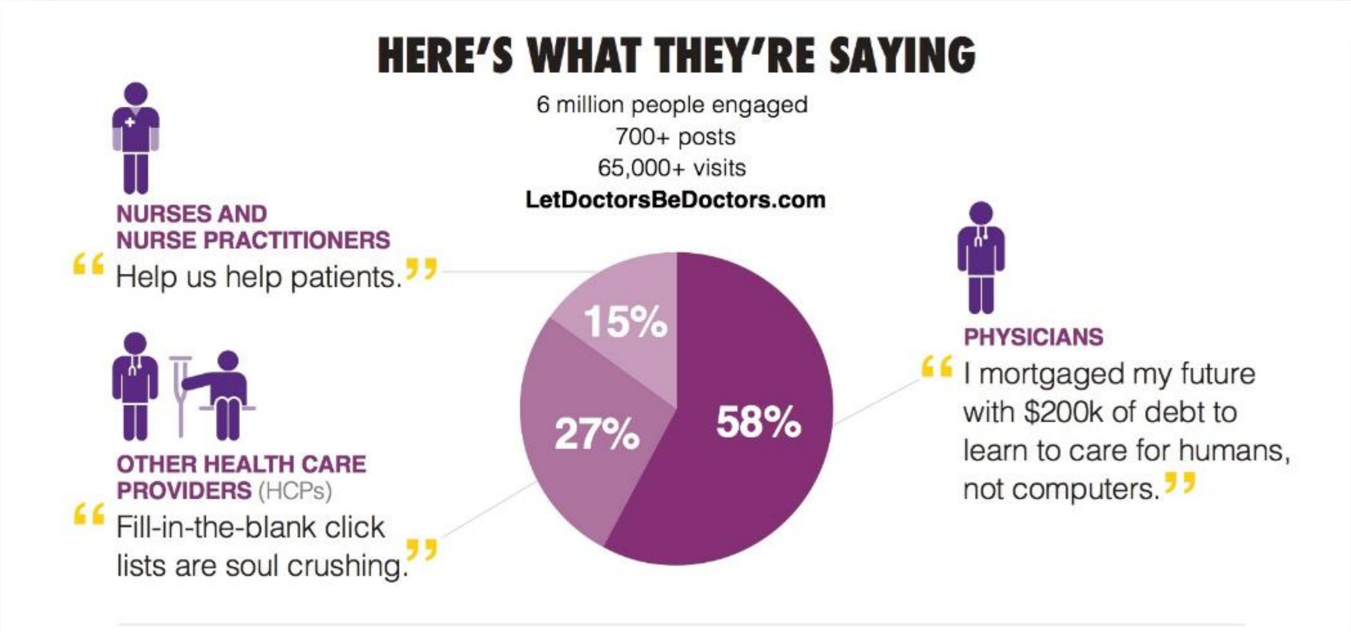
Table. US Patient Cohorts Used for Training Clinical Machine Learning Algorithms, by State[a]

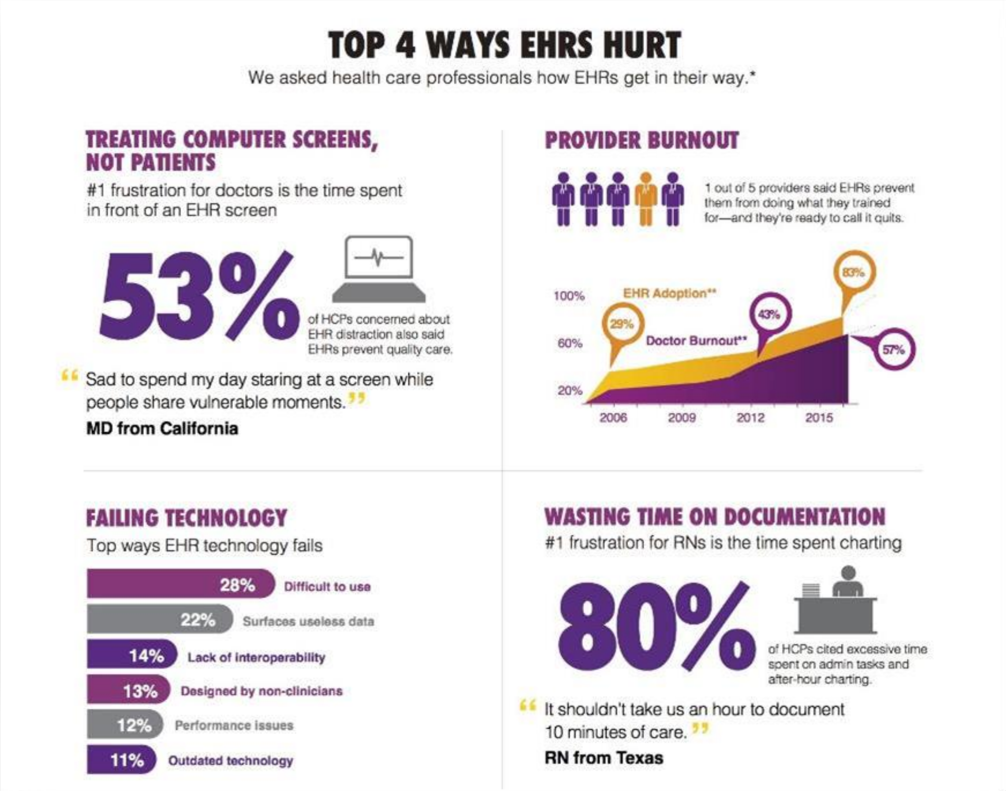
States	No. of studies
California	22
Massachusetts	15
New York	14
Pennsylvania	5
Maryland	4
Colorado	2
Connecticut	2
New Hampshire	2
North Carolina	2
Indiana	1
Michigan	1
Minnesota	1
Ohio	1
Texas	1
Vermont	1
Wisconsin	1

US Patient Cohorts Used for Training Clinical Machine Learning Algorithms, by State[aa] Fifty-six studies used 1 or more geographically identifiable US patient cohorts in the training of their clinical machine learning algorithm. Thirty-four states were not represented in geographically identifiable cohorts: Alabama, Alaska, Arizona, Arkansas, Delaware, Florida, Georgia, Hawaii, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Maine, Mississippi, Missouri, Montana, Nebraska, Nevada, New Jersey, New Mexico, North Dakota, Oklahoma, Oregon, Rhode Island, South Carolina, South Dakota, Tennessee, Utah, Virginia, Washington, West Virginia, and Wyoming.

JAMA. 2020;324(12):1212-1213. doi:10.1001/jama.2020.12067

Why Nurses Hate EHRs





Standardized Code Sets

overly specific codes = better research or burnout?

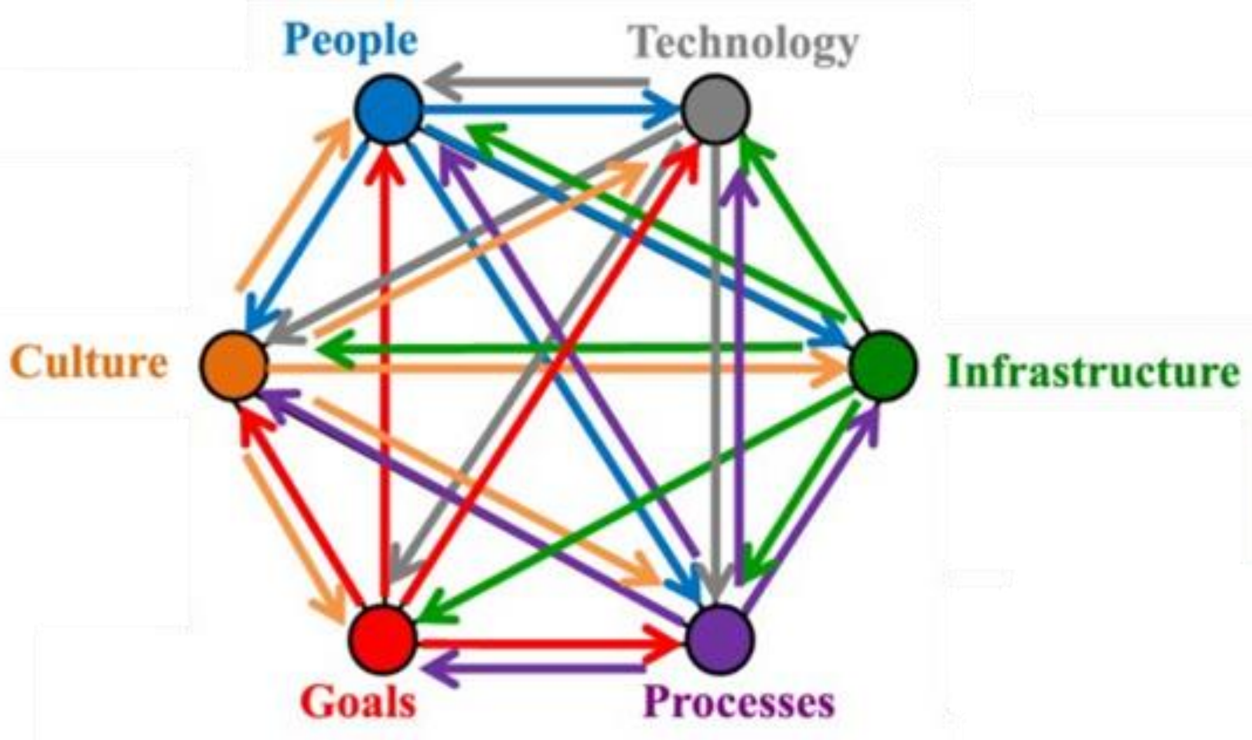
- W59.22XS: Struck by a turtle, sequela
- W22.02XD: Walked into lamppost, subsequent encounter
- Y93.E2: Injury due to activity – laundry
- R46.0: Very low level of personal hygiene
- R46.1: Bizarre personal appearance
- **Z60.4 - Social exclusion and rejection**

- V91.07XD: Burn due to water-skis on fire, subsequent encounter
- V90.22: Drowning and submersion due to jumping from a burning fishing boat
- Y35.419D: Legal intervention involving bayonet, unspecified person injured, subsequent encounter

- **Z63.1: Problems in relationship with in-laws**

Addressing the Gaps

Making AI Work: A Sociotechnical Lens



- Many technologies have failed when deployed into complex healthcare settings
- One cause of these failures is the difficulty accounting for the collaborative and exception-filled nature of medical work
- Collaboration is key to identifying the kinds of challenges that lead to unanticipated breakdowns and eventual abandonment

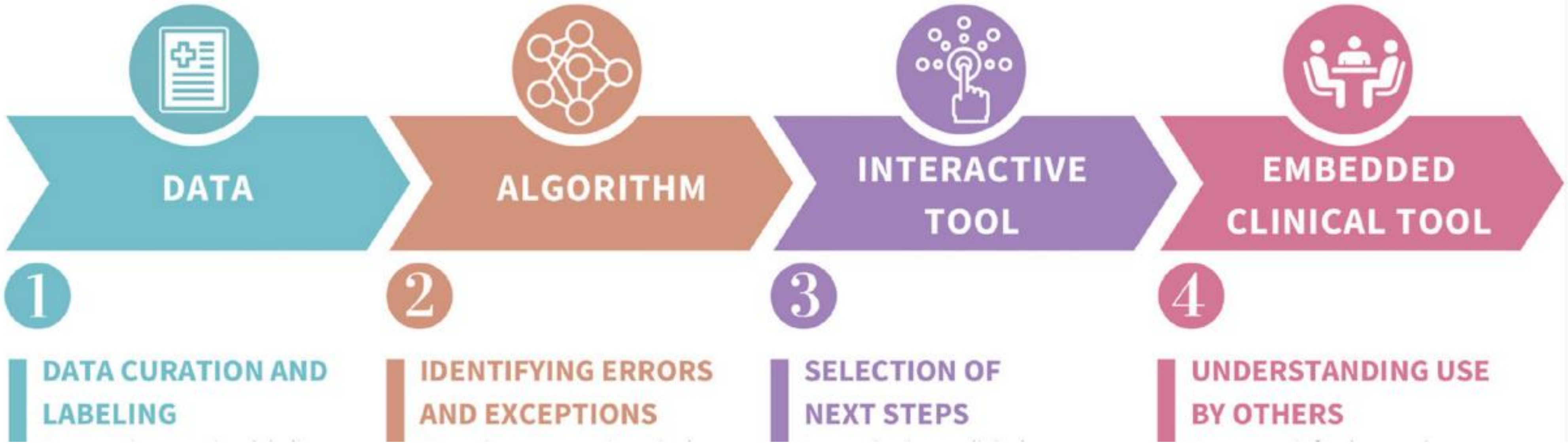
Clegg, Chris W., et al. "Applying organizational psychology as a design science: A method for predicting malfunctions in socio-technical systems (PreMiSTS)." *Design Science* 3 (2017).

Comparison of AI-Based and Human-Decision Making

Decision-making conditions	AI-Based Decision Making	Human Decision Making
Specificity of the decision	Requires a **well-defined decision search** space with specific functions	Can accommodate a **loosely defined** decision search space
Interpretability of decision-making process and outcome	Complexity of the functional forms make it difficult to **interpret the decision process and outcomes**	Decisions are **explainable** and **interpretable**, though vulnerable to retrospective sense-making
Size of the alternative dataset	Can accommodate **large alternative sets**	**Limited capacity** to uniformly **evaluate** a **large** alternative set
Speed	Relatively **fast**. **Limited tradeoff** between **speed** and **accuracy**	Comparatively **slow**. **High** trade-off between **speed** and **accuracy**
Replicability of outcomes	Decision-making process and outcomes are **highly replicable** due to computational procedures	Vulnerable to inter- and intra- individual factors like **expertise**, **attention**, **context**, and **emotional** state

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational Decision-making Structures in the Age of Artificial Intelligence. *California Management Review*, *61*(4), 66-83.

How clinical expertise can drive successful integration of AI in healthcare



Ulloa M, Rothrock B, Ahmad FS and Jacobs M (2022) Invisible clinical labor driving the successful integration of AI in healthcare. Front. Comput. Sci. 4:1045704. doi: 10.3389/fcomp.2022.1045704

How clinical expertise can drive successful integration of AI in healthcare

DATA CURATION AND LABELING

Data curation: the process of collecting data about a particular problem
Data labeling: classifying each data sample, which is then used to train models
Data validation: compares model outputs against ground truth methods (e.g., expert analysis)

All steps require clinical expertise

Real-world example:

- Machine learning model developed to predict stage C or stage D heart failure
- Used a dataset of 14,846 patients
- Data labeling and curation approach: Chart review involving multiple electronic medical records (Epic, Care Everywhere) to ensure a thorough understanding of what's going on with the patient.
- Data validation approach: 416 patients were reviewed by a clinical coordinator, and agreement between the coordinator and model was measured

Cheema, Baljash, R. Kannan Mutharasan, Aditya Sharma, Maia Jacobs, Kaleigh Powers, Susan Lehrer, Firas H. Wehbe et al. "Augmented intelligence to identify patients with advanced heart failure in an integrated health system." JACC: Advances 1, no. 4 (2022): 1-11.

How clinical expertise can drive successful integration of AI in healthcare

IDENTIFYING ERRORS AND EXCEPTIONS

Algorithms will never be perfect due to erroneous predictions and exceptional cases
A common approach is to present a model's output to a clinical expert who will make a final determination

Real-world example:

- Machine learning model developed to predict stage C or stage D heart failure
- Model classified a patient as stage D heart failure
- Nurse coordinator reviewed the patient's chart. Patient had been hospitalized five times, but it was due to COVID. But they had now fully recovered.

Challenge:

- Identifying errors may be more difficult for healthcare providers than making decisions independently, without influence from algorithm output.

Ulloa M, Rothrock B, Ahmad FS and Jacobs M (2022) Invisible clinical labor driving the successful integration of AI in healthcare. Front. Comput. Sci. 4:1045704. doi: 10.3389/fcomp.2022.1045704

How clinical expertise can drive successful integration of AI in healthcare

SELECTION OF NEXT STEPS

Clinical AI output often does not directly translate into healthcare decisions.

Clinical team members are likely the best at translating model output to care decisions, especially in light of potential algorithmic errors

Real-world example:

- Used machine learning to identify patients with depression at risk of dropping out of treatment
- Clinicians recommended a workflow which initiated the involvement of a broader care team who could follow up with patients more frequently if patient was at risk of dropout.

Challenge:

- Clinicians demonstrated differing abilities to connect predictions to actionable next steps

Ulloa M, Rothrock B, Ahmad FS and Jacobs M (2022) Invisible clinical labor driving the successful integration of AI in healthcare. Front. Comput. Sci. 4:1045704. doi: 10.3389/fcomp.2022.1045704

How clinical expertise can drive successful integration of AI in healthcare

UNDERSTANDING USE BY OTHERS

This includes understanding how model outputs are intended to support team goals and how individuals interpret results for clinical decisions

Ulloa M, Rothrock B, Ahmad FS and Jacobs M (2022) Invisible clinical labor driving the successful integration of AI in healthcare. Front. Comput. Sci. 4:1045704. doi: 10.3389/fcomp.2022.1045704

Designing where, when, and how to make and integrate AI-clinical tools

To enhance the practice of ethical and responsible AI in medicine

A need for more:

- Documentation of labor
- Clear workflows
- Knowledge of team structures

Ulloa M, Rothrock B, Ahmad FS and Jacobs M (2022) Invisible clinical labor driving the successful integration of AI in healthcare. Front. Comput. Sci. 4:1045704. doi: 10.3389/fcomp.2022.1045704

Translating science into implementation


Healthcare IT News

Research suggests Epic Sepsis Model is lacking in predictive power

A retrospective study in JAMA Internal Medicine finds that the model did not identify two-thirds of sepsis patients and frequently issued false alarms.

By Kat Jercich | June 22, 2021 | 12:44 PM

Healthcare is local and every care setting is unique.

Implementing new technology requires considerations of current tools, people and work context.

THE PATH FORWARD FOR AI IN HEALTHCARE

Bridging Technology and Nursing Gaps

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