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Precision Education: The Future of Lifelong Learning in Medicine

(aka the “Why, What, and How” of Precision Education)

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NYU Grossman School of Medicine

@ jbrafel

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Will Small (Medicine)


Omar Moussa (Medicine)


Carl Drake (Medicine)


Sandy Zabar (Medicine)

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Learning Objectives (& Disclosures)

At the end of this session, participants will:

- **Why**: Recognize the confluence of societal and medical education *needs* driving a desire for greater precision is medical education
- **What**: Describe a "precision education" *conceptual framework* that applies for individuals, programs, or health systems
- **How**: Identify needed *data and analytic capacities* for academic health systems to actualize precision education

Disclosures – Dr. Rafel declares the following activities:

- Research support from the NBME and AMA
- Research consultant for ScholarRx, a medical education company

WHY

—

Precision Education

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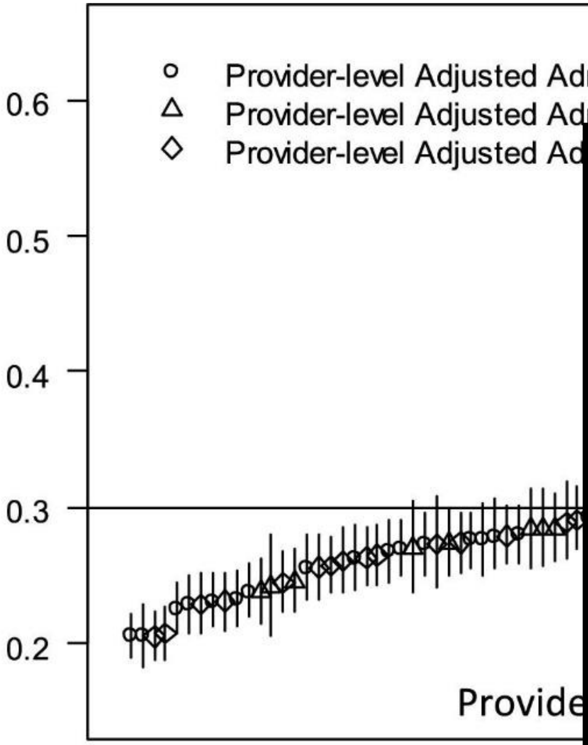
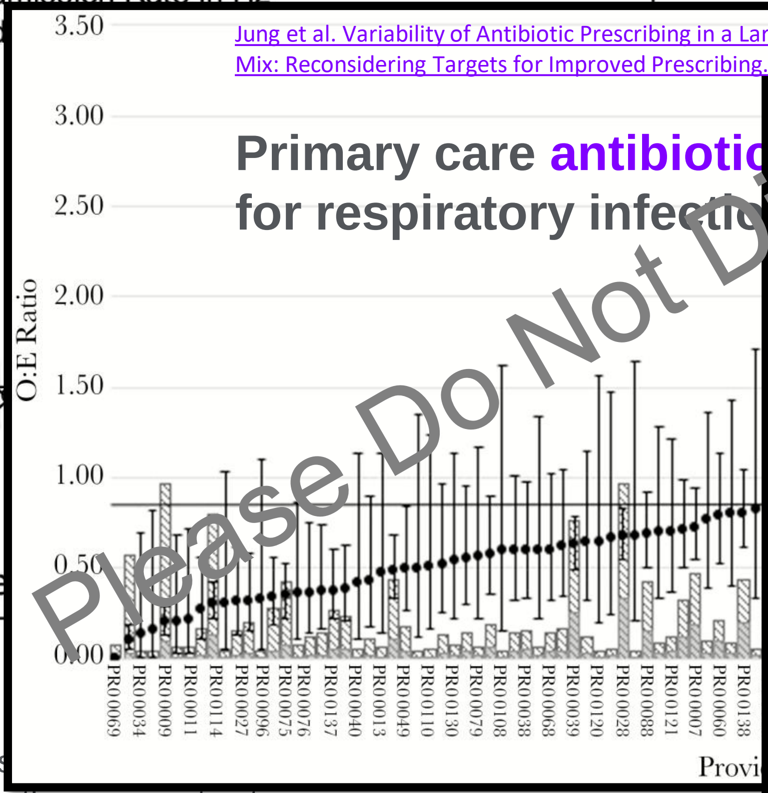
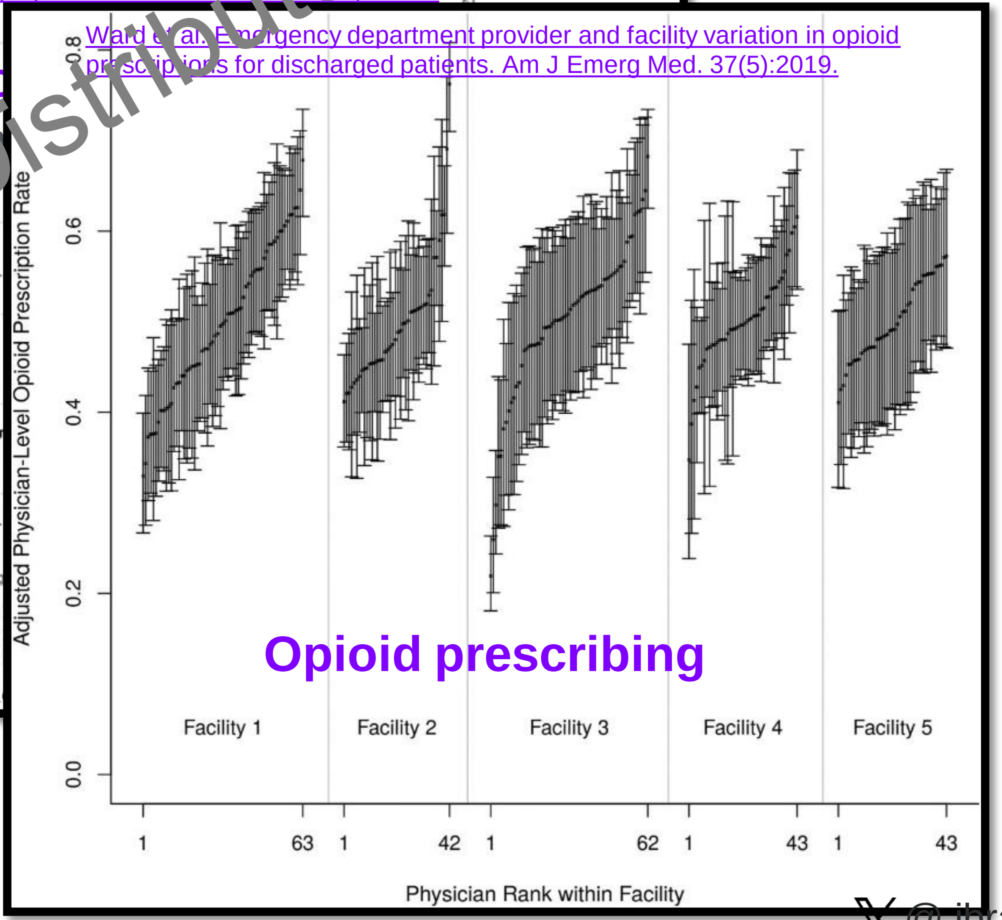
UNIVERSAL IMAGES GROUP VIA GETTY IMAGES

Honoring our Social Contract? Unwanted Physician-Level Variation in Care

Admission rate across 3 EDs by physician







Adjustments: patient age, sex, arrival day/time.
Clustering: patients within phys repeated patient encounters by the same patient.

Abualenain J et al. Emergency department physician-level and hospital-level variation in admission rates. Annals of emergency medicine. 2013 61(6):638-43.

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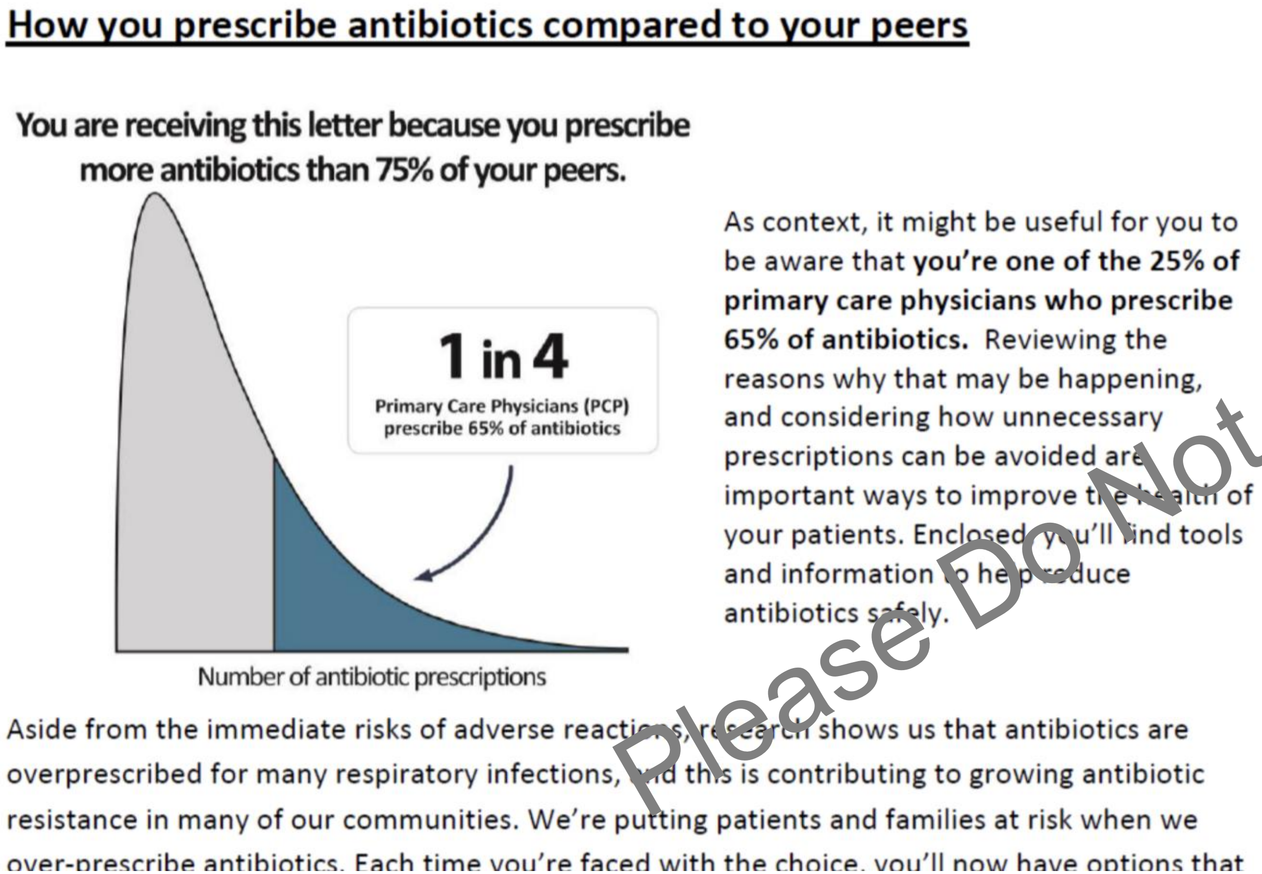
Teaching Old Dogs New Tricks … Or Not



How you prescribe antibiotics compared to your peers

As context, it might be useful for you to be aware that **you're one of the 25% of primary care physicians who prescribe 65% of antibiotics.** Reviewing the reasons why that may be happening, and considering how unnecessary prescriptions can be avoided are important ways to improve the health of your patients. Enclosed you'll find tools and information to help reduce antibiotics safely.

Aside from the immediate risks of adverse reactions, research shows us that antibiotics are overprescribed for many respiratory infections, and this is contributing to growing antibiotic resistance in many of our communities. We're putting patients and families at risk when we over-prescribe antibiotics. Each time you're faced with the choice, you'll now have options that

Highest quartile antibiotic-prescribing PCPs in Ontario, Canada 2018

Randomized:
Letter (n = 3000) vs. no letter (n = 500)

Initiation letter

- RR 0.96; 97.5% CI, 0.92-1.01 (ns)

Duration letter

- RR 0.95; 97.5% CI, 0.91-1.00 (P=.01)

This isn't just Canada…20% of US PCPs account for 70% of opioid prescriptions to older adults

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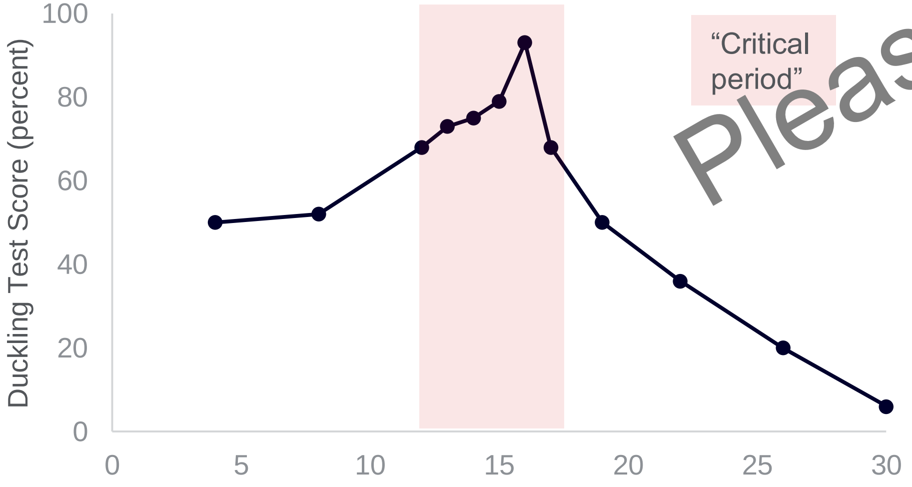
Schwartz KL et al. Effect of antibiotic-prescribing feedback to high-volume primary care physicians on number of antibiotic prescriptions: a randomized clinical trial. JAMA Intern Med. 2021.

High-Quality, Equitable Care Starts in Training … and Persists Durably

Konrad Lorenz – "Imprinting"



(Adapted from Hess)

Evaluating Obstetrical Residency Programs Using Patient Outcomes

David A. Asch, MD, MBA
Sean Nicholson, PhD
Sindhu Srinivas, MD, MSCE
Jeph Herrin, PhD
Andrew J. Epstein, PhD, MPP

Context Patient outcomes have been used to assess the performance of hospitals and physicians; in contrast, residency programs have been compared based on non-clinical measures.

Objective To assess whether obstetrics and gynecology residency programs can be evaluated by the quality …

Design, Setting, and Patients A retrospective analysis of all Florida and New York

JAMA. 2009;302(12):1277-1283.

The Effects of Training Institution Practice Costs, Quality, and Other Characteristics on Future Practice

Robert L. Phillips, Jr, MD, MSPH[1]
Stephen M. Petterson, PhD[2]
Andrew W. Bazemore, MD, MPH[2]
Peter Wingrove, BS[2]
James C. Puffer, MD[1]

ABSTRACT

PURPOSE Medicare beneficiary spending patterns reflect those of the 306 Hospital Referral Regions where physicians train, but whether this holds true for smaller areas or for quality is uncertain. This study assesses whether cost and quality i… (HSAs), 82.4 …

Ann of Fam Med. 2017; 15(2):140-148.

Original Investigation

Spending Patterns in Region of Residency Training and Subsequent Expenditures for Care Provided by Practicing Physicians for Medicare Beneficiaries

Candice Chen, MD, MPH; Stephen Petterson, PhD; Robert Phillips, MD, MSPH;
Andrew Bazemore, MD, MPH; Fitzhugh Mullan, MD

JAMA. 2014;312(22):2385-2393.

Performance Follows a Learning Curve … If You Can Measure It

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Dreyfus SE, Dreyfus HL. A five-stage model of the mental activities involved in directed skill acquisition. Berkeley, CA: University of California; 1980. Report No.: ORC 80-2.

Kalet A., M Pusic. 2014. Defining and Assessing Competence. In: Kalet A., Chou C. (eds) Remediation in Medical Education. Springer, New York, NY.

Howard NM, DA Cook, R Hatala, MV Pusic. Learning Curves in Health Professions Education Simulation Research: A Systematic Review. *Simul in Healthcare.* 2021;16(2):128-135.

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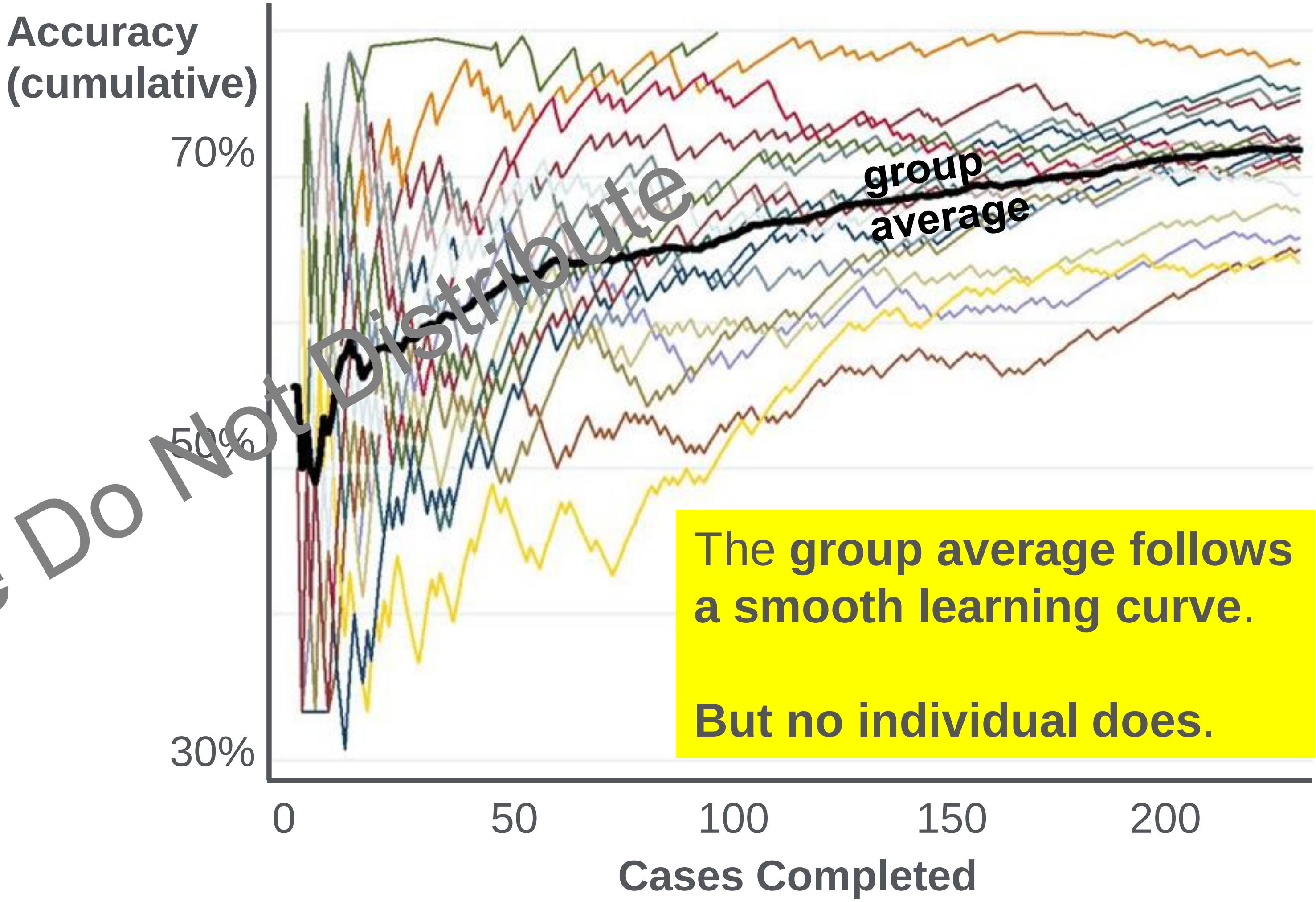
Performance Follows a Learning Curve … If You Can Measure It

18 peds residents, 234 ankle x-rays

Definitely abnormal ↔ Definitely normal



The **group average follows a smooth learning curve.**

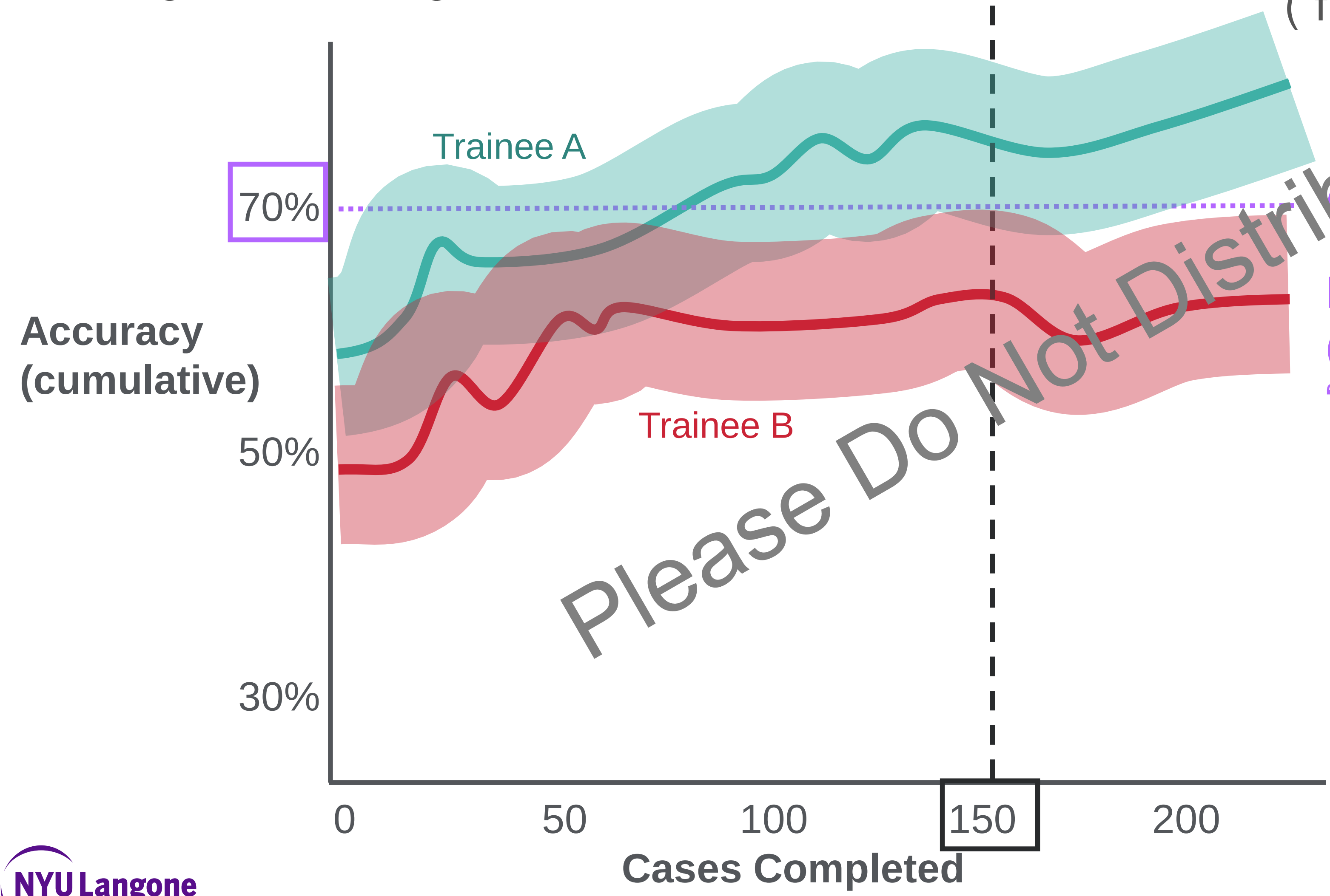
But no individual does.

Pusic M, K Boutis, R Hatala, D Cook. Learning Curves in Health Professions Education. *Academic Medicine.* 2015;90(8):1034-42.

Adapted from: Learning Curve Theory and Its Implications for CBME: Inter-Individual Variability

Competency-Based Education: Mastery-Based Learning

Trainees rating ankle x-rays: differing prior knowledge and learning rates



At the mercy of inter-individual variability ("fixed time, variable outcome")

Competency Based

Endpoint set by achievement ("time variable, fixed outcome" "mastery-based learning")

Real world (current state): imprecision in measuring learning curve limits sound early judgments on progress toward competence

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Adapted from: [Learning Curve Theory and Its Implications for CBME: Inter-Individual Variability]

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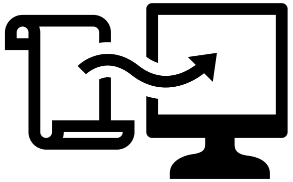
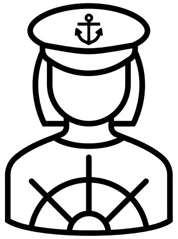
Every Trainee Can and Should be Exceptional . . . But How?

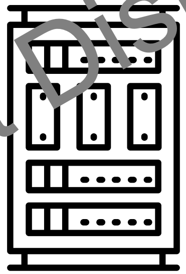


Longitudinally integrated, meaningful, high-density data about trainees

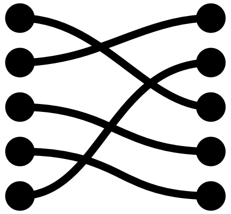


Educators, coaches empowered by **predictive analytics and AI**

Assessments focused on **behaviors and outcomes**



Systems, technology to power analytics and handle complexity



Flexible pathways for competency-based progression

Individual-level precision in how we teach, coach, assess, credential

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WHAT

Precision Education

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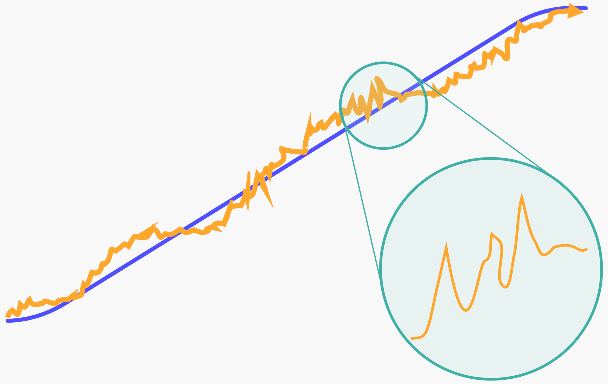
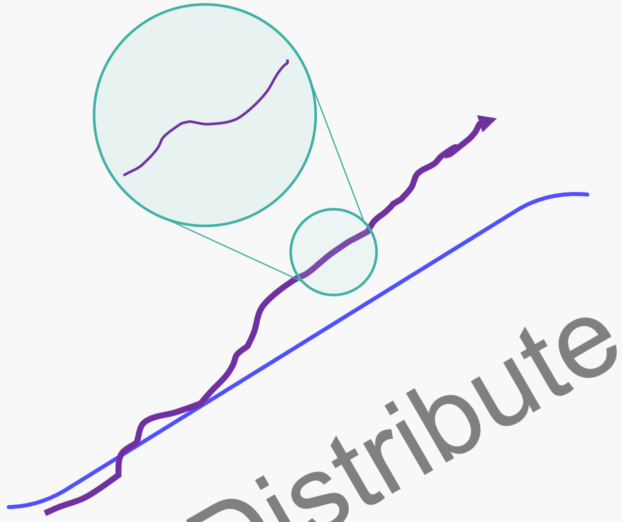
Building *system* of **precision education**…





… **defines** the curve
accelerates learning
smooths the path

Precision Medical Education is a *systematic approach* that integrates **longitudinal data and analytics** to drive **precise educational interventions** addressing each **individual learner's needs and goals** in a continuous, timely, and cyclical fashion — ultimately **improving meaningful educational, clinical, and system outcomes.**

Adapted with permission from Sanjay Desai, MD

Triola MM, Burk-Rafel J. Precision Medical Education. *Academic Medicine*. 2023.

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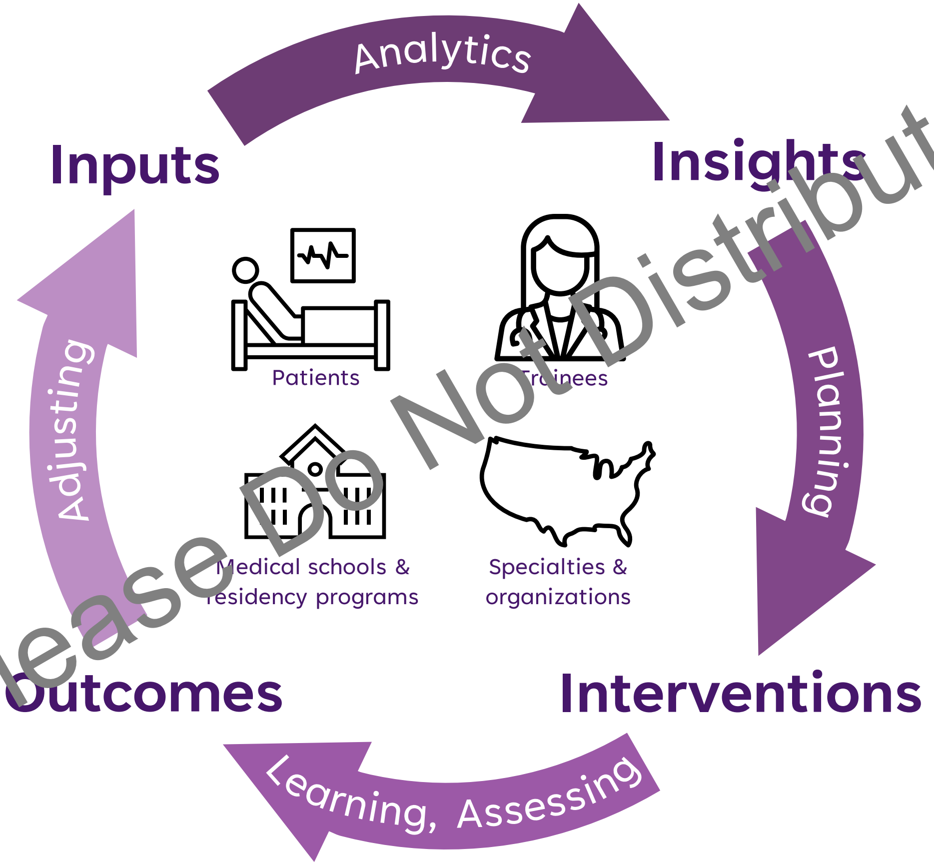
AI and other advanced **analytics**

Multifaceted **data aggregation**

Preliminary findings and **visualizations**



Make **adjustments** to precision education cycle

Iteratively refine through **co-production**

Measure distal outcomes and **impact**

Precision education **intervention** – educational resource, assessment, coaching

Gather **feedback** and assess proximal outputs / outcomes

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Desai et al. Precision Education: The Future of Lifelong Learning in Medicine. *Acad Med.* 2024.
Triola & Burk-Rafel. Precision Medical Education. *Acad Med.* 2023.

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HOW

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Precision Education Inputs / Outcomes

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Evaluations & Assessments

- Exams (preclinical, shelf, USMLE, ITE, certification)
- OSCEs
- EPAs, OPAs, Milestones
- …

Experiences & Educational Exposures

- Case/procedure logs
- Simulations
- Curricular content, sequencing
- Advising, goals
- …

Transitions & Handovers

- Admissions: AMCAS, ERAS
- ILPs
- Coaching handovers
- …

Precision Education Data Hub

Trainees

Education Data Warehouse

Data Scientists & Informaticists

Clinical & Educational Experts

Programs

In-Training Clinical Data

Epic

- EHR metadata (e.g. Signal)
- Diagnostic exposures
- Attributable care measures (RSQMs, TRACERs)
- Traditional CPMs (e.g. HEDIS)
- …

Unsupervised Practice

- Claims-based practice patterns
- Faculty appointments
- Research grants
- Workforce measures
- …

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Evaluations & Assessments

Experiences & Educational Exposures

Transitions & Handovers

CCC Comment Analysis
Summarization, classification of narrative comments to reduce rater effects on CCC decisions.
~**Marin, Ludlow**

Clinical Exposures & ITE
Diagnostic exposures linked to board content areas.
~**Drake, Sartori**

Educational Resource Nudges
Resources (podcasts, schemas) sent to learners based on patient diagnoses.
~**Triola, Moussa**

Transition to Residency Advantage
UME-to-GME "bridge" coaching. GenAI integration to guide shadowing, SMARTer goals.
~**Winkel**

Visual Diagnosis: ECGs
Learning curves and visual diagnosis assessment.
~**Oh**

Empathy Assessment
Using multimodal data and GenAI to assess and coach empathy.
~**Yoncheva**

ICDs to Board Outlines
Generalized approach for mapping ICD-10 to board content areas.
~**Malhotra, Sagalowsky**

Admission Essays & ChatGPT
Changes to admission essays (UME and GME) post-ChatGPT.
~**Park**

AI for Admissions
ML and NLP for medical student and resident selection.
~**Rafel, Triola**

In-Training EHR Data

Unsupervised Practice

Resident Ordering TRACER
Resident-attributable care patterns captured using SQL queries for diabetes ordering patterns. ~**Rafel, Kinnear**

Interprofessional Communication Patterns
Network analysis applied to EHR metadata to characterize resident interprofessionalism.
~**Small**

IIME Precision Education Hub

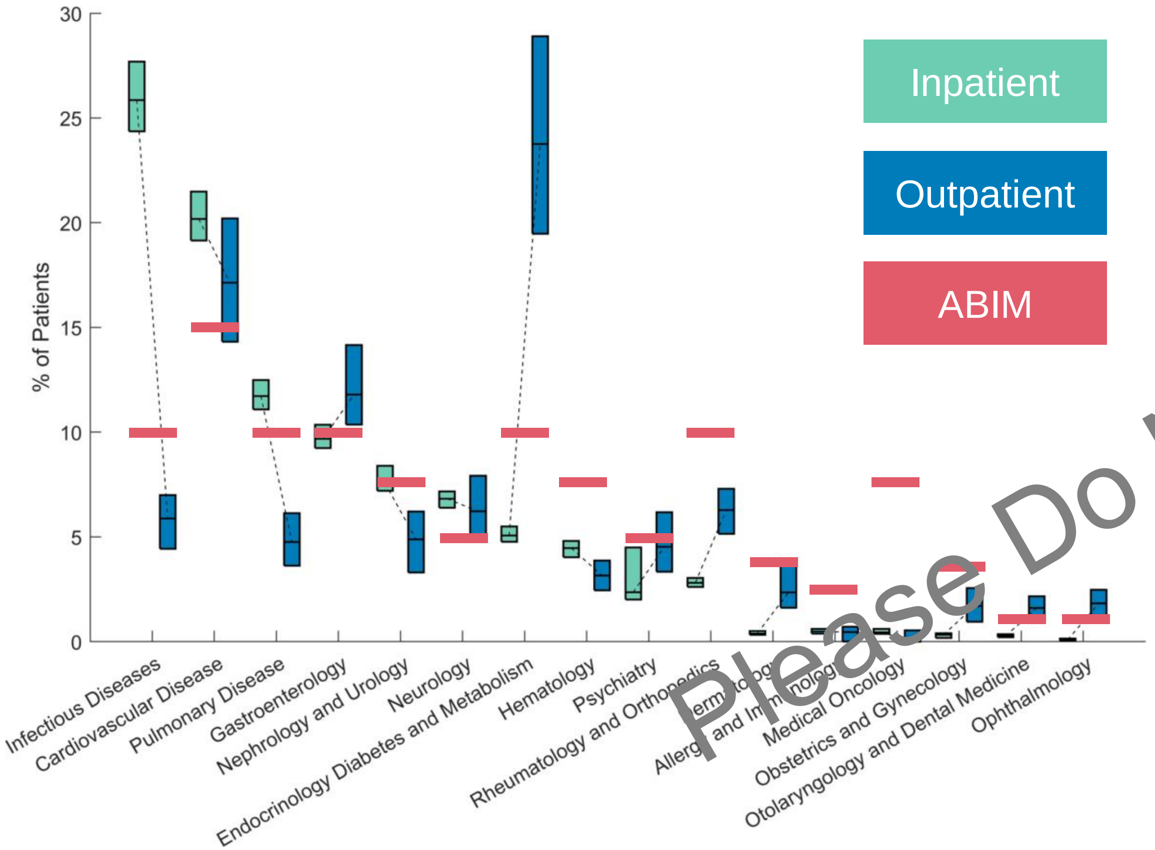
Graduates into Practice: AMA *Graduate Profile*
Report to medical schools and residency programs on graduate workforce, outcomes.
~**Rafel, Richardson**

NoteSense Clinical Reasoning Feedback
LLM-assessed clinical reasoning documentation quality provided to residents for every admission H&P. ~**Schaye**

Diagnostic Accuracy (DiagnosisAId)
Identifying missed diagnostic opportunities with GenAI.
~**Schaye, Sartori**

PMIDs of Representative Papers
ECG (Oh): 32986084, 35086115, 33913438
Clinical Experiences (Drake/Sartori): 33983144, 35752814, 39103985
Nudges (Triola/Moussa): 38113440
Coaching (Winkel): 38109650, 36652456, 37683265
Admissions (Rafel/Triola): 36888969, 34348383, 36940395
T2DM TRACER (Rafel/Kinnear): 37215538
SecureChat (Small): 38147337
Clinical Reasoning (Schaye): 33945113, 35710676, 38166201
Graduates (Rafel/Richardson): 34705676, 38166211

Harnessing Clinical Care Data: Trainee Exposure Variation



- ICD-10 to ABIM domain crosswalk
- 51 IM residents at NYULH Brooklyn campus (2020-2023)
- 152,420 clinical encounters
- Clinical experiences enriched in ID and cardiology
- Very little allergy, dermatology, oncology, or rheumatology
- Some trainees: 2x cases in a given area as peers
- Little concordance between actual frequency of clinical experience and ABIM certification exam content frequency

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Drake et al. Toward precision medical education: Characterizing individual residents' clinical experiences throughout training. JHM. 2024.

What is “Precision” in Assessment?

Increasing assessment: breadth, sources, density, longitudinality, contextuality, clinical relevance

“Assumes you know where the pixels go & how they sit in relationship…
[But competence is] a jigsaw without the box it came in” ~Dr. Derek Louey (@dymonite69)

“I find assessment constructs prematurely close on a particular part of the [picture]…” Dr. Cory Rohlfsen (@CoryRohlfsen)

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Adapted from Lambert Schuwirth and Cees van der Vleuten; @nora_leopardi; 3D from the Louvre

Inputs / Outcomes: Emerging Approaches … Coming to a Program Near You!

	Expert Observation	Learning Analytics & EHR Measures	Tech-Enhanced Skill Measurement
	WBAs **OSCEs**	**RSQMs & TRACERs** **EHR metadata**	**Wearables** **Motion & location capture**
	Scouting, game film	Wins above replacement (WAR), On-base percentage (OBP)	Pitch spin rate, Hit launch angle
	Gold standard, multi-source feedback	Objective, quantifiable, often scalable	Natively attributable, quantifiable, high-density
	Bias, subjectivity, assessor workload	Data integration, attribution, interdependence, intangibles	Logistics, cost, context assessment, intangibles

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Kinnear et al. Finding Medicine's Moneyball. *Acad Med*. 2024.

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RSQMs — Resident-Sensitive Quality Measures

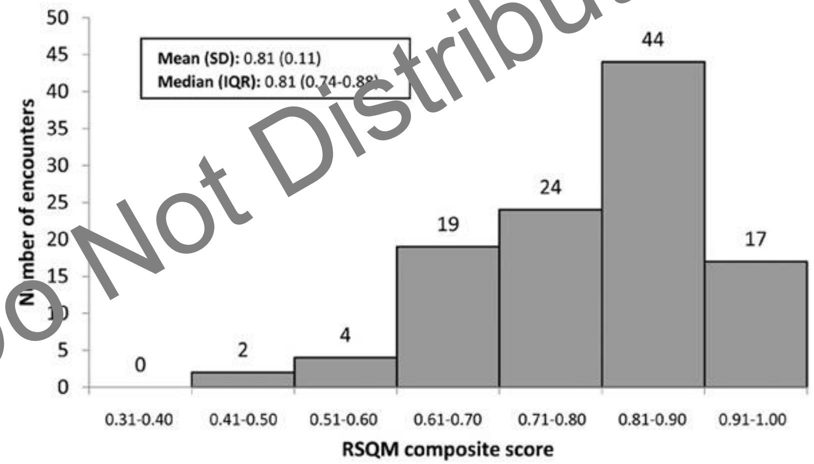
Meaningful

For patient care and trainees

Attributable

To an individual trainee

Peds EM Residents: Asthma Exacerbation



- 83 PEM residents, 112 encounters
- Chart review RSQM bundle
  - 63 Resident-Sensitive Quality Measures
  - (21 asthma, 23 bronchiolitis, 19 head injury)

Order
- ✓ Asthma order set
- ✓ Albuterol dose
- ✓ Dexamethasone used
- ✓ Dexamethasone dose
- ✓ …

Document
- ✓ Acuity
- ✓ Prior intubation
- ✓ Work of breathing
- ✓ Air exchange
- ✓ …

Discharge
- ✓ Standard dosing
- ✓ Steroid instructions
- ✓ Follow-up stated
- ✓ …

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Schumacher et al. Developing Resident-Sensitive Quality Measures. *Acad Med.* 2018.
Schumacher et al. Initial Implementation of Resident-Sensitive Quality Measures in the Peds ED. Acad Med. 2020.
Burk-Rafel et al. TRainee Attributable & Automatable Care Evaluations in Real-time (TRACERs). *Perspect Med Ed*. 2023.

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Harnessing Clinical Care Data: Trainee Performance Variation

IM Residents: Clinical Reasoning

Human-rated notes (R-IDEA scale)

↓

AI (ML, NLP, LLM)

↓

Automated algorithm

Low vs. **High quality** clinical reasoning documentation in resident H&Ps

Representative Notes from Two Trainees

Lower-Quality Clinical Reasoning Documentation

42 y.o. male admitted to the medicine service for alcohol withdrawal and **epigastric pain, likely alcohol gastritis.**

#**epigastric pain, likely alcohol gastritis**
-troponin negative X2, EKG without ischemic changes
-s/p Zofran 4mg iv, Pepcid 20mg iv, Maalox 30ml
-c/w Pepcid bid

Higher-Quality Clinical Reasoning Documentation

82 y/o f w/ CAD s/p CABD, PPM, aflutter, HTN, HLD, CKD, COPD p/w chest pain for several days and EKG changes.

#**chest pain**: pt reports several days of intermittent chest pain which is at least partly reproductive with palpation; **initial troponin negative which lowers suspicion for ACS given timeframe from onset of symptoms**. Third trop elev to 0.04 may be fluctuating around baseline. **However, in this patient with h/o CABG and new EKG findings, lower threshold for further evaluation. D-dimer negative, lower suspicion for PE.**

Core Entrustable Professional Activity

- ✓ *EPA 2*: Prioritize a differential diagnosis following a clinical encounter
- ✓ *EPA 5*: Document a clinical encounter in the patient record

ACGME Competency

- ✓ *Patient Care 3*: Clinical Reasoning
- ✓ *Interpersonal and Communication Skills 3*: Communication within Health Care Systems

Trainees rarely receive formal training about (or assessment of) their documentation, despite desiring training and feedback

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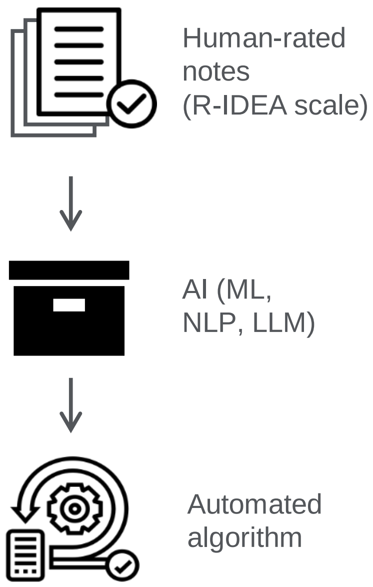
- Weber et al. Improving trainee clinical documentation through a novel curriculum in internal medicine. J Hosp Med. 2022 Jan;17(1):28-35.
- Aylor et al. Resident notes in an electronic health record: a mixed-methods study using a standardized intervention with qualitative analysis. Clin Pediatr. 2017; 56(3): 257-262.
- Oxentenko et al. Time spent on clinical documentation a survey of internal medicine residents and program directors. Arch Intern Med. 2010; 170(4): 377-380.
- Isoardi et al. Exploration of the perceptions of emergency physicians and interns regarding the medical documentation practices of interns. Emerg Med Australas. 2013; 25(4): 302-307.
- Crotty et al. Open notes in teaching clinics: a multisite survey of residents to identify anticipated attitudes and guidance for programs. J Grad Med Educ. 2018; 10(3): 292-300.

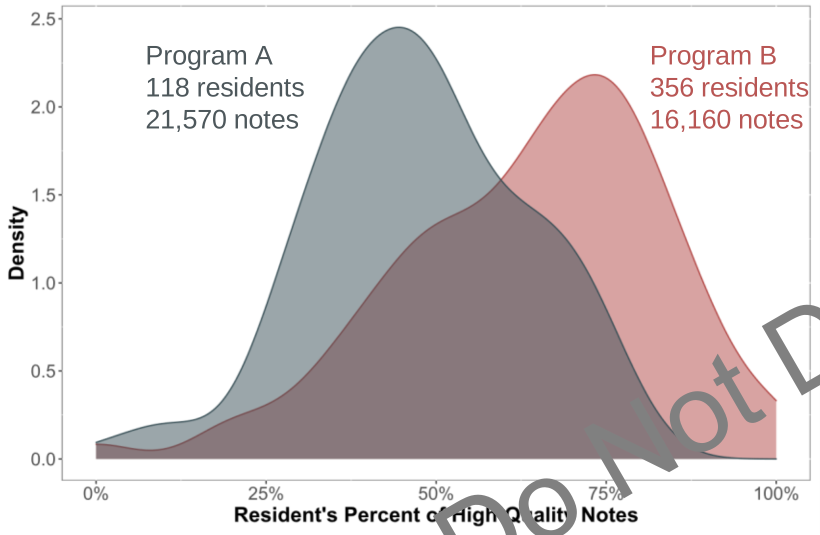
Harnessing Clinical Care Data: Trainee Performance Variation

Please do not distribute this slide

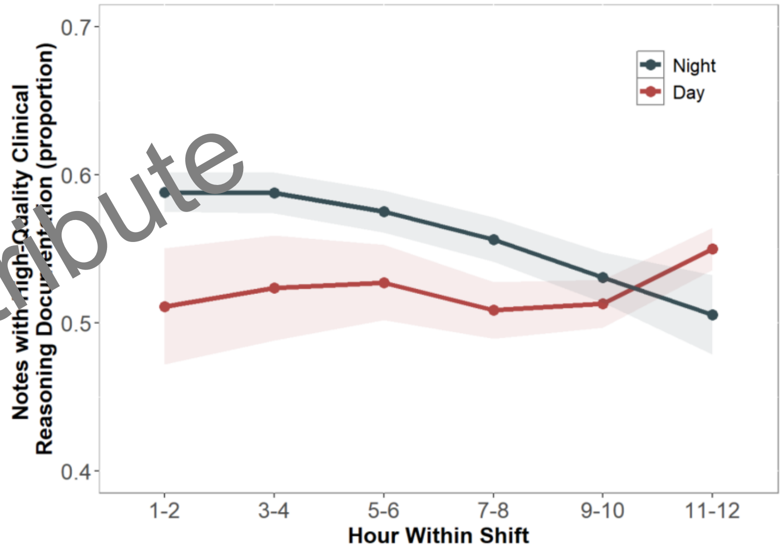
IM Residents: Clinical Reasoning

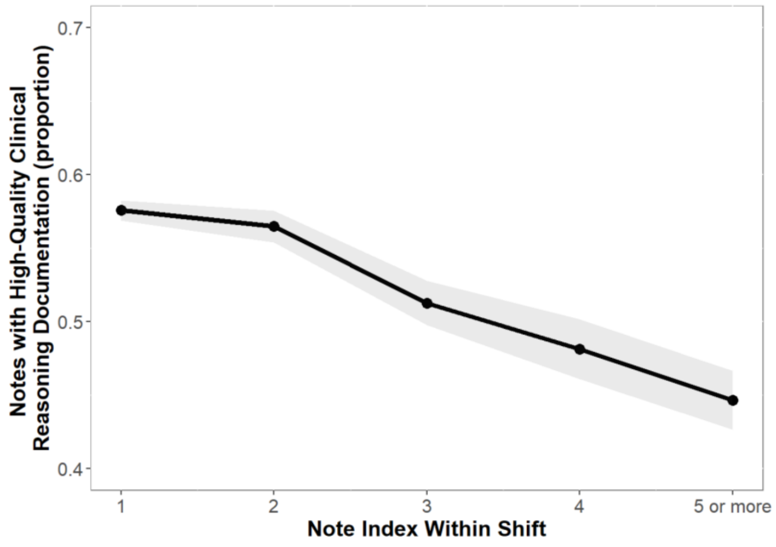


Low vs. **High quality** clinical reasoning documentation in resident H&Ps



- AI-based TRACER
  - (TRainee Attributable & Automatable Care Evaluation in Real-time)
- 474 NYULH IM residents
- 28,782 patients; 37,750 notes





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NBME

Support: Stemmler Fund

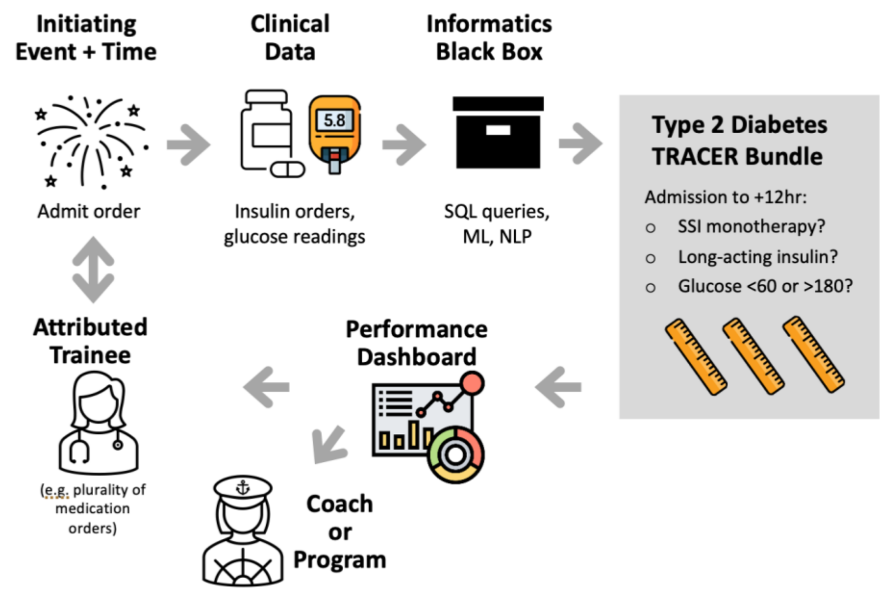
University of Cincinnati

Michigan Medicine

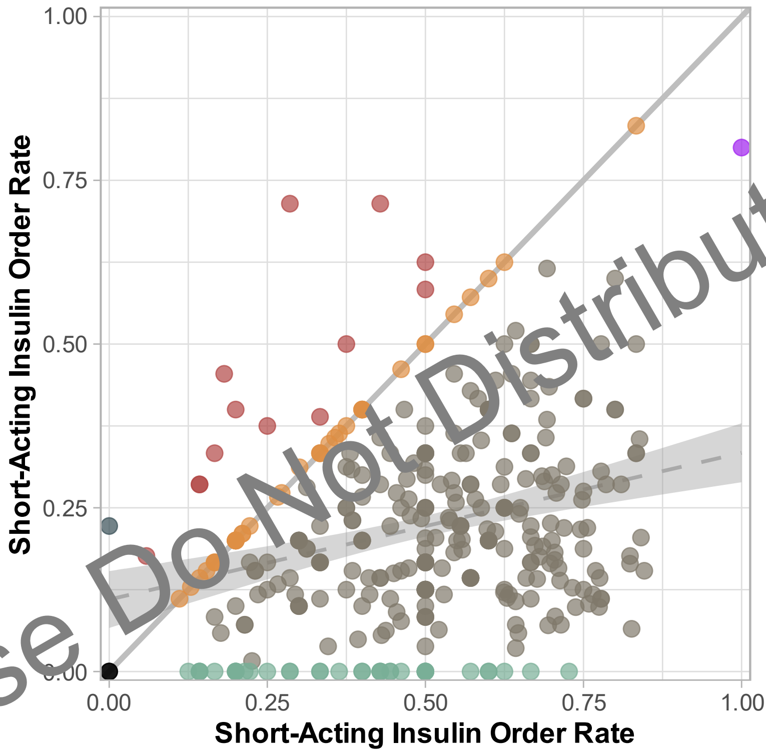
Schaye et al. *J Gen Intern Med.* 2022;37(9):2230-2238.

Harnessing Clinical Care Data: Trainee Performance Variation

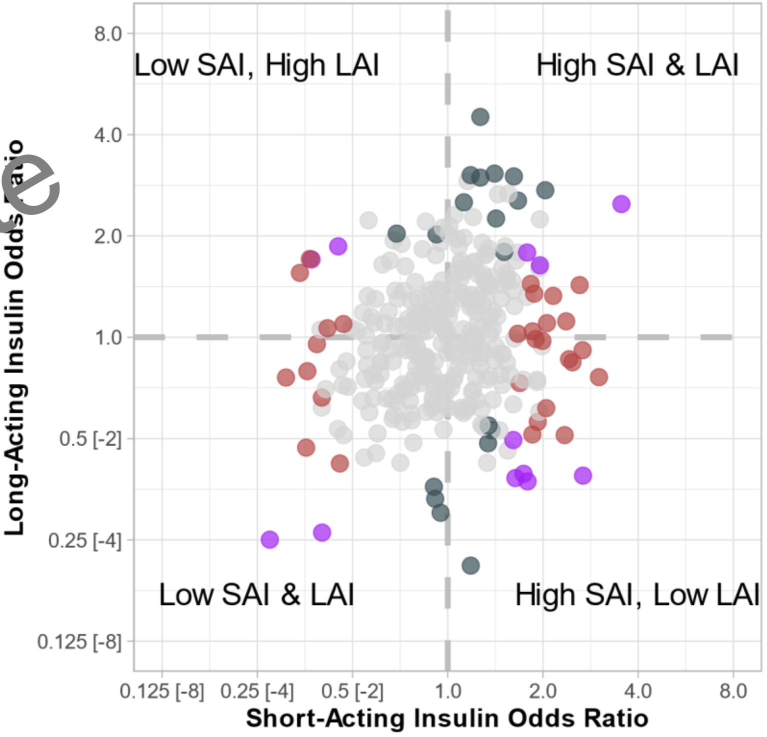
IM Residents: Insulin for T2DM



- SQL-based TRACER
- 503 NYULH IM residents (331 with >5 encounters)
- 6,070 distinct patients
- 7,850 T2DM encounters
- 4,438 short-acting insulin (SAI) and 1,631 long-acting insulin (LAI) orders



Phenotype	Residents (n)
Favor Short-Acting (~2:1)	238
Short-Acting ≈ Long-Acting	40
Never Long-Acting	36
Favor Long-Acting	13
Never Insulin	2
Always Short-Acting	1
Never Short-Acting	1



**Adjusted for: site, patient random effects, T2DM risk group, sex, age, insurance, Charlson comorbidity index, primary diagnosis, glycemic team involvement*

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University of Cincinnati
Stanford Medicine

AMA

Support: AMA ChangeMedEd

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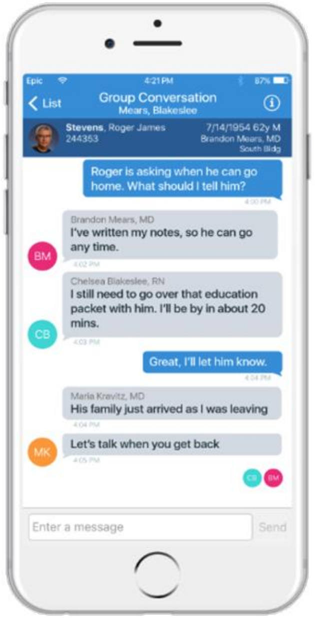
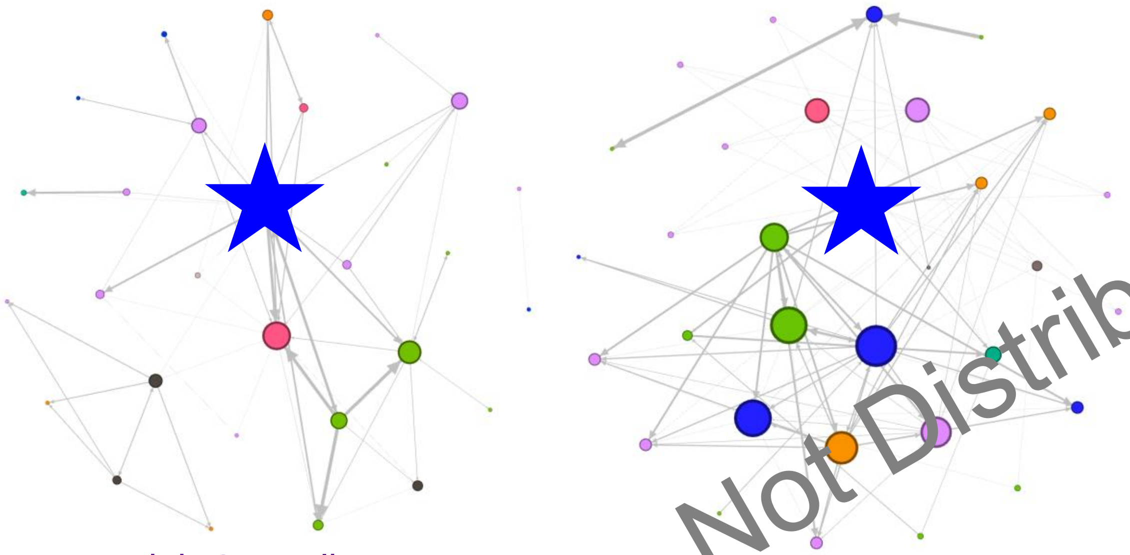
Inputs / Outcomes: EHR Metadata



15M messages / year;
200 per hospitalization

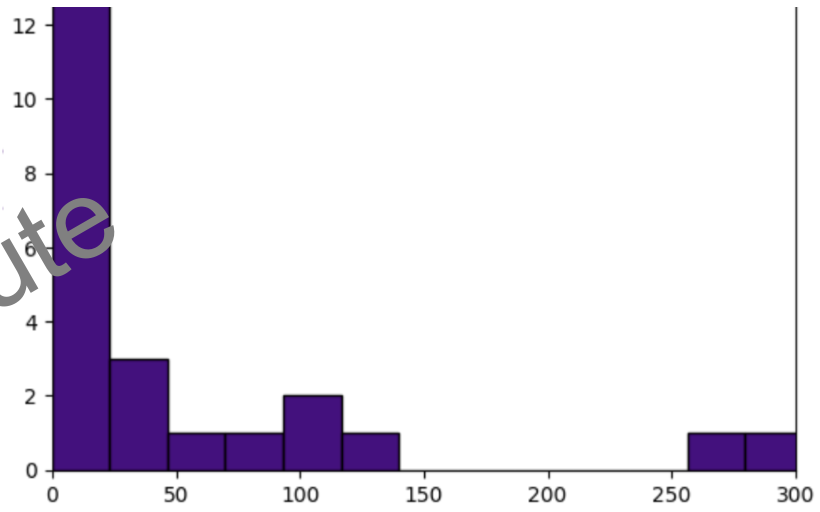
Two Hospitalizations Attributed to Single IM Resident



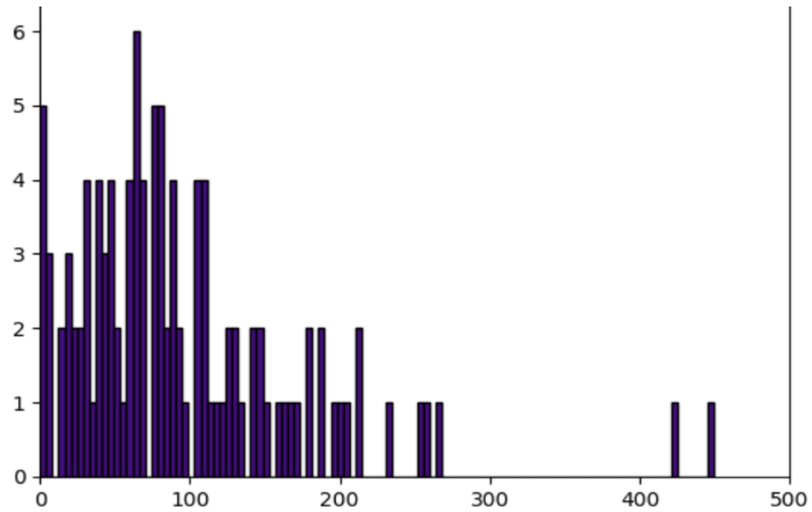
High Centrality

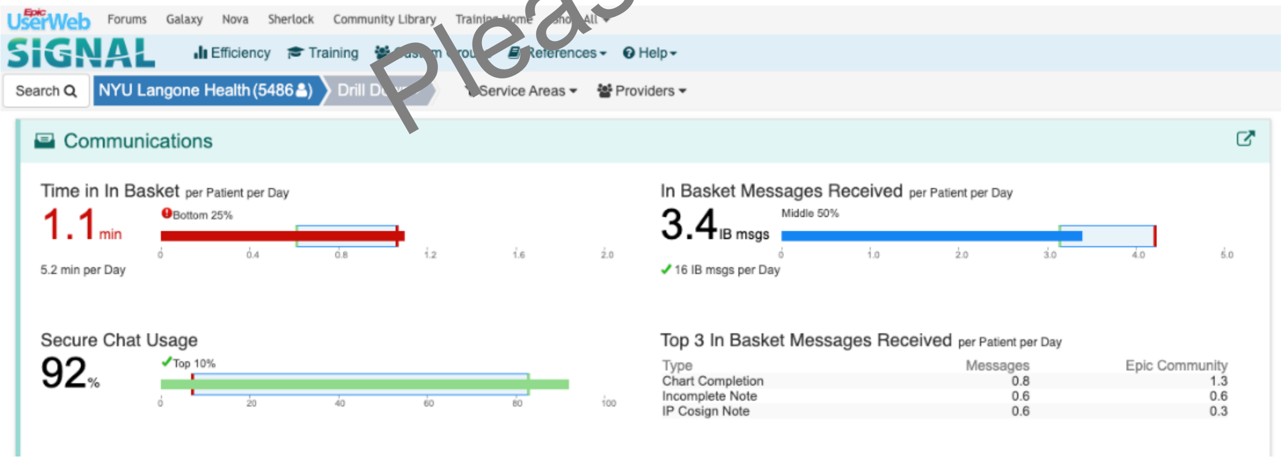
Low Centrality

Intra-Intern Variation: Centrality



Inter-Intern Variation: Centrality





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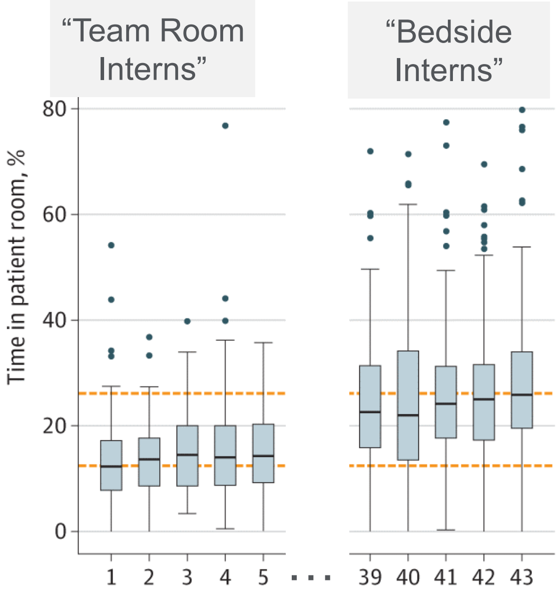
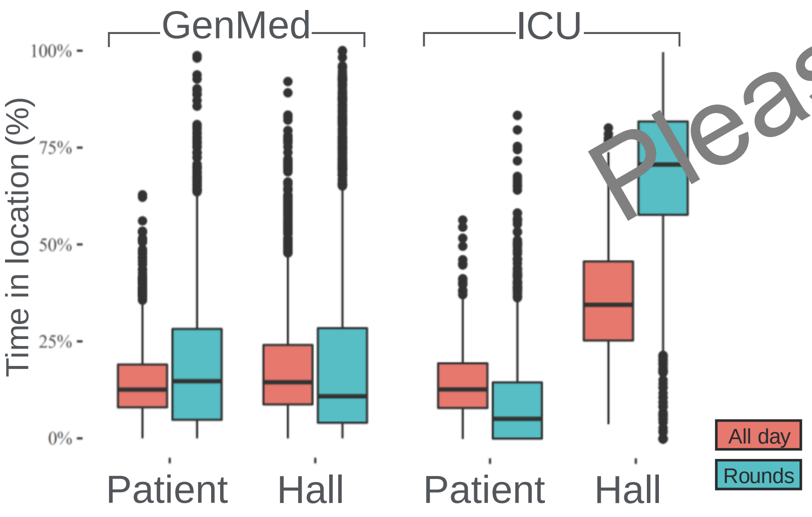
Inputs / Outcomes: Technology-Enhanced Skill Measurement

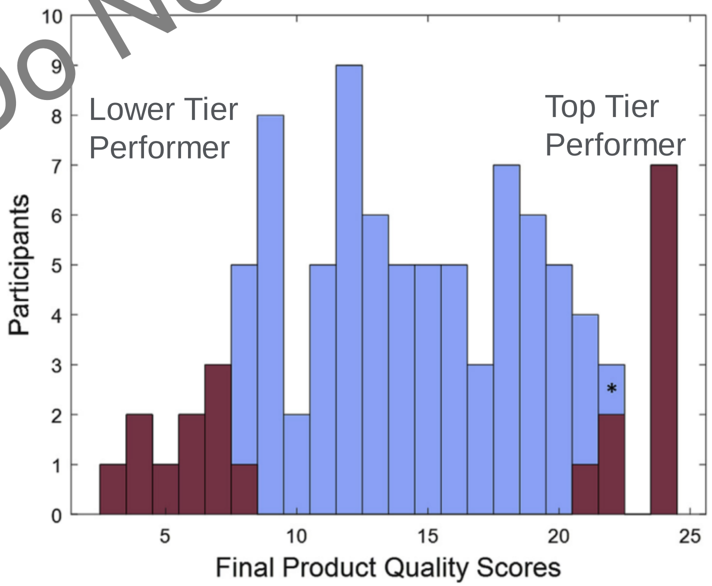
Real-Time Location Tracking (Brian Garibaldi)

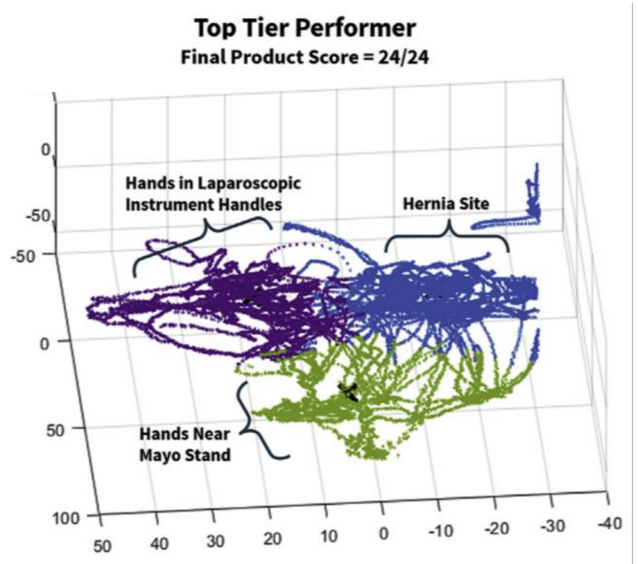


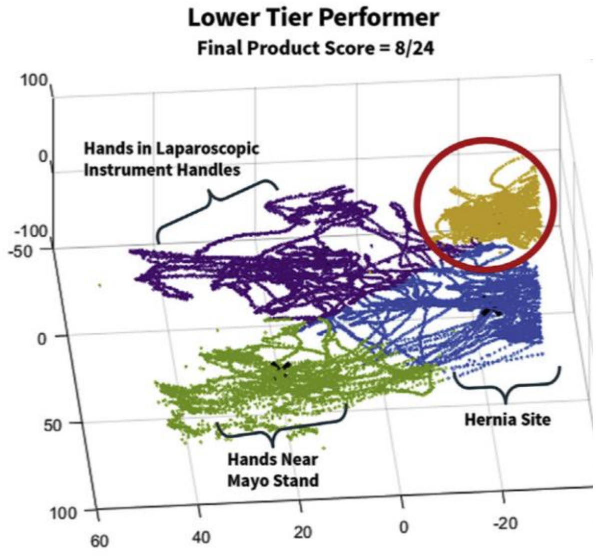


Rosen et al. *JAMA Netw Open*. 2022;5(6):e2215885.

Motion Tracking & Haptics (Carla Pugh)







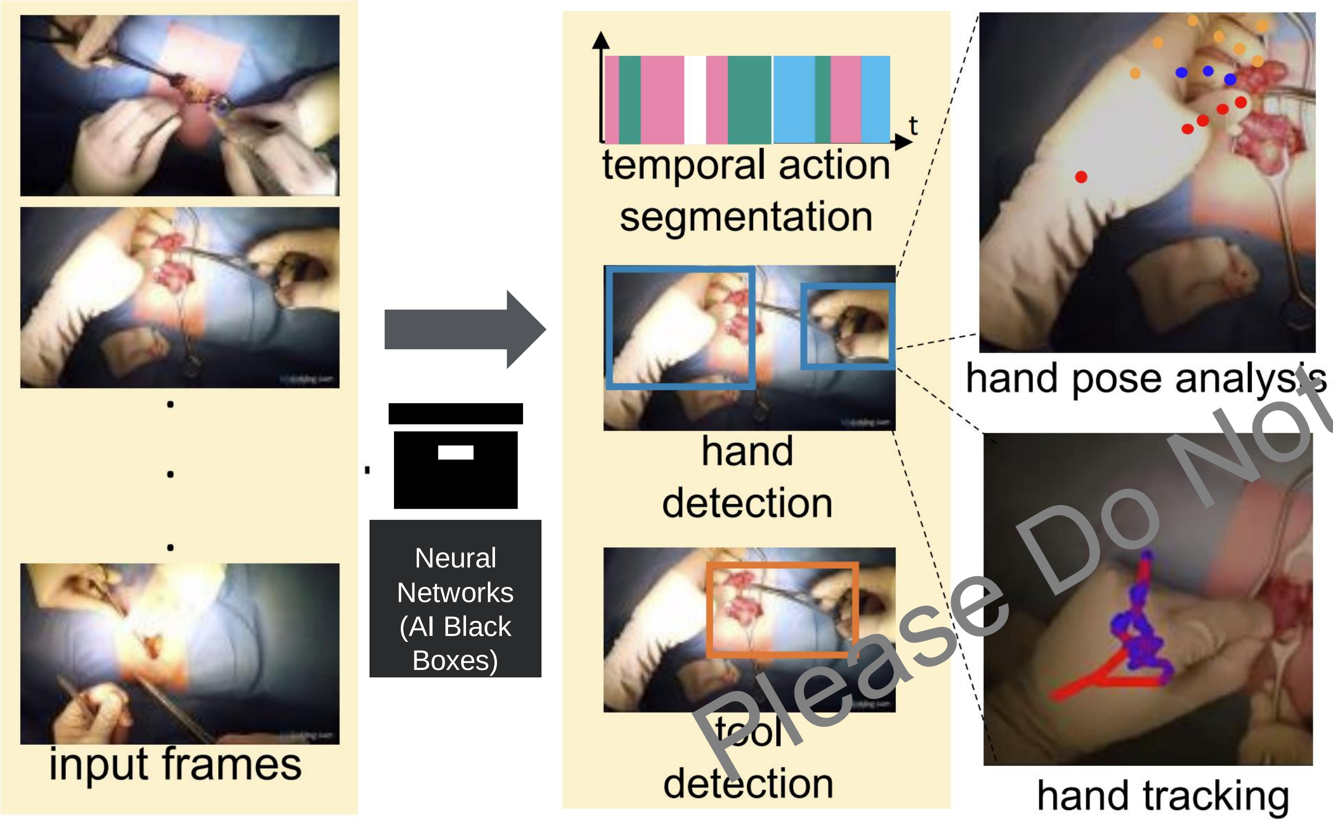
Stanford MEDICINE

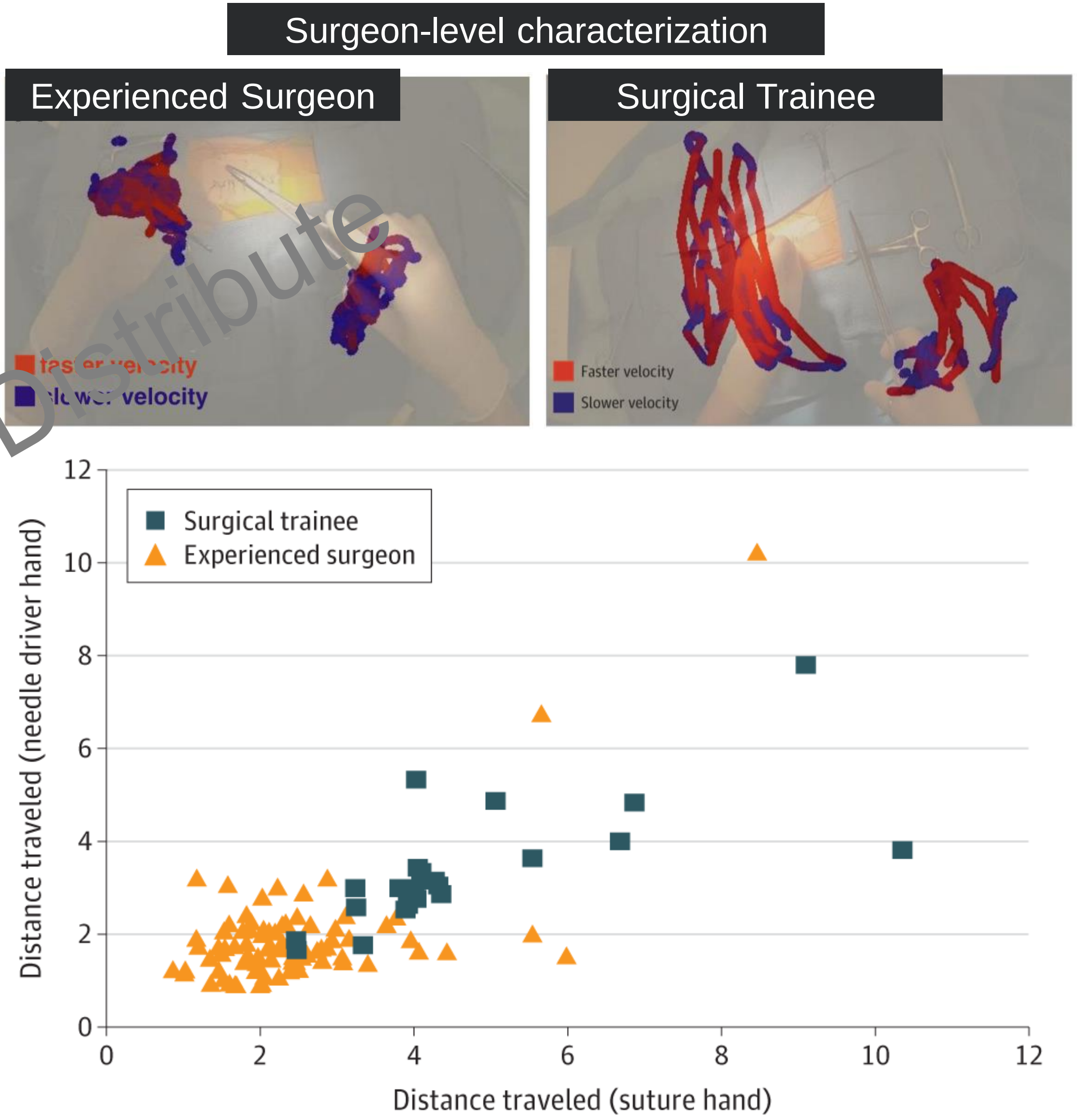
Perrone et al. *Am J Surg*. 2020;219(4):552-556.

X @ jbrafel

Inputs / Outcomes: Technology-Enhanced Skill Measurement

Computer Vision (Brat & Yeung-Levy)





Model training: 1997 open surgery YouTube videos from 50 countries over last 15 years.

NYU Langone Health

Goodman et al. Analyzing Surgical Technique in Diverse Open Surgical Videos With Multitask Machine Learning. *JAMA Surg*. 2024;159(2):185-192.

@ jbrafel

Inputs / Outcomes: Distal Clinical Care Measures – The “Final Product”

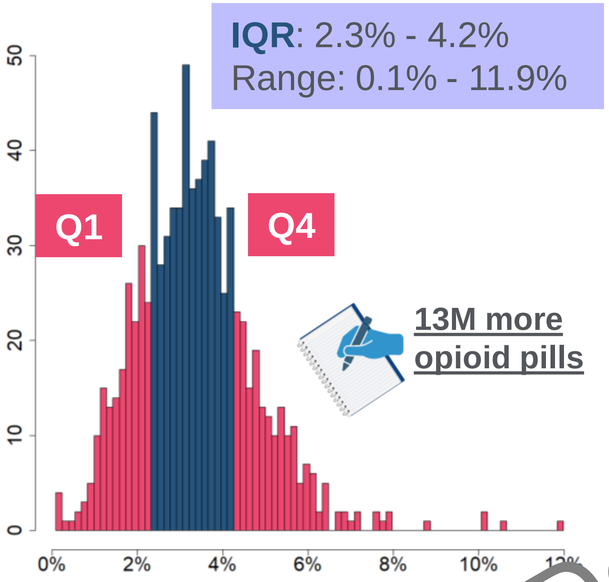
Please do not distribute this slide

Milestones to Outcomes

840 Programs

12,671 PCPs

5M Opioid prescriptions



Program-Level Opioid Prescription Rate
(Opioid Prescriptions / Total Prescriptions)

ML model Q1 vs. Q4 programs: **AUROC 0.86**

- **Patient** comorbidities
- Practice **region**
- Graduates’ **Milestone ratings** (small)
- Programs’ Milestone **rating patterns** (moderate) – surrogate for faculty development?

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AMA

Support: AMA ChangeMedEd

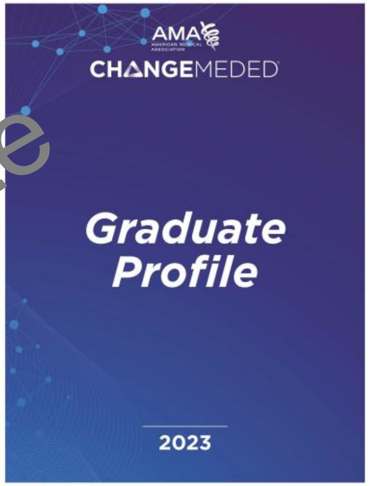
ACGME

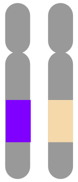
AMA Graduate Profile

148 Schools
400+ Programs

750,000 Graduates

4.7B Medicare prescriptions





NYU “gene” (or epigene)

	Other Medical School & Other Residency [Reference] Mean	Physicians (Prescriptions per Physician)	NYU Medical School & Other Residency Mean	Physicians (Prescriptions per Physician)	Other Medical School & NYU Residency Mean	Physicians (Prescriptions per Physician)	NYU Medical School & NYU Residency Mean	Physicians (Prescriptions per Physician)
Opioid Prescription Rate	4.2%	78,062 (474)	2.8%	260 (427)	2.0%	149 (265)	1.5%	68 (202)
Brand Name Prescription Rate	11.7%	87,607 (1,382)	13.5%	320 (1,455)	16.9%	246 (1,239)	15.6%	113 (1,034)

HOW

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Precision Education Analytics

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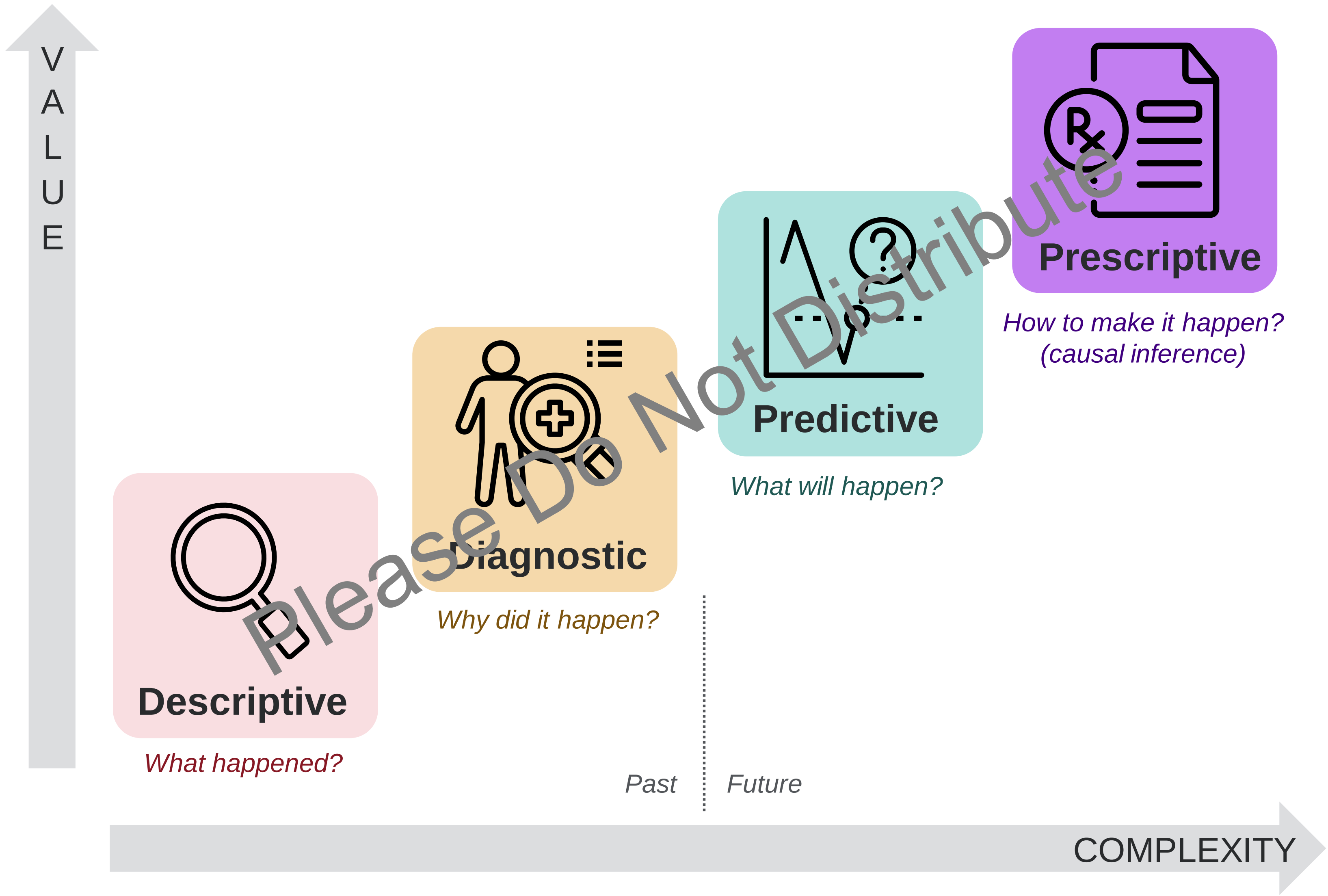
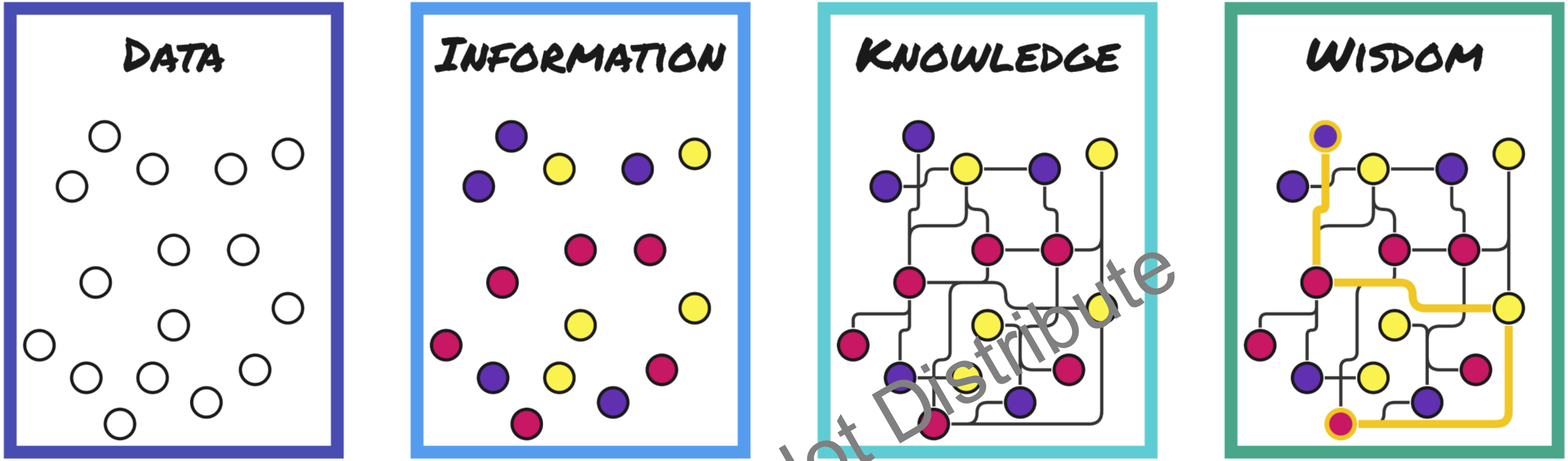
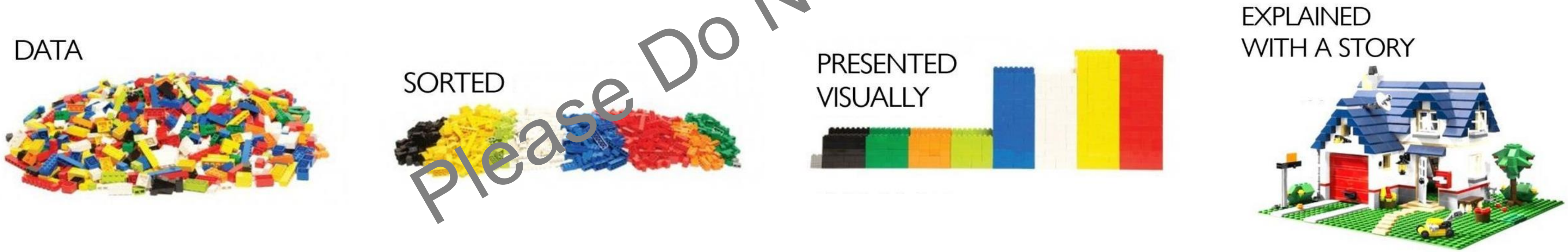
Analytics: Maturity Model







Student performance across the assessments

Student performed poorly on medical knowledge (MK) exams and then failed USMLE

Consistently poor MK exam performance likely indicates gaps in knowledge and might lead to high-stakes exam failure

Based on MK performance, student has 2x odds of USMLE failure

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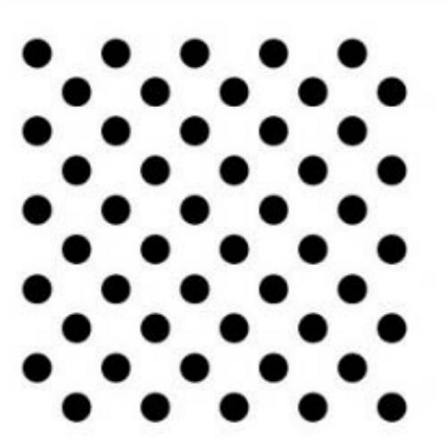
[From Data to Wisdom: The DIKW Journey]

X @ jbrafel

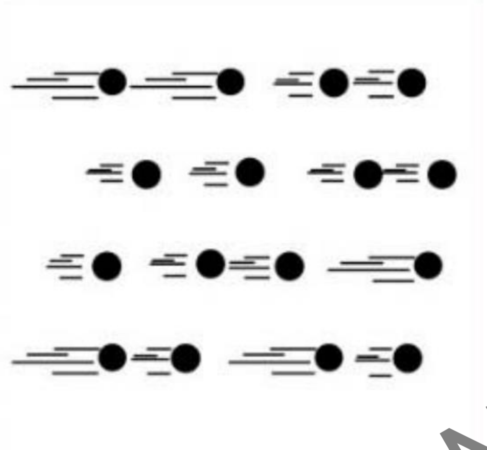
Volume



Data at Rest

Terabytes+ of data to process

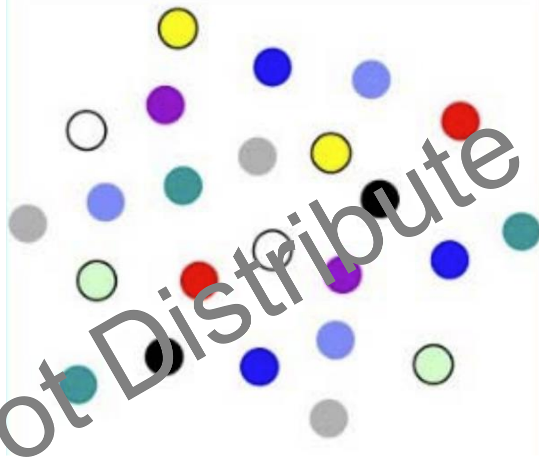
Velocity



Data in Motion

Constantly accruing, requiring timely response

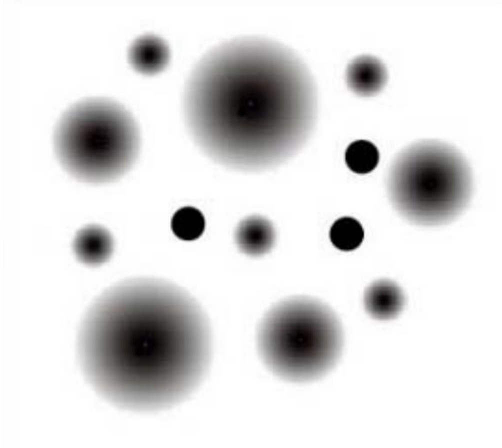
Variety



Data in Many Forms

Structured, unstructured, text, multimedia

Veracity



Data in Doubt

Uncertainty due to inconsistency, incompleteness, ambiguities, latency

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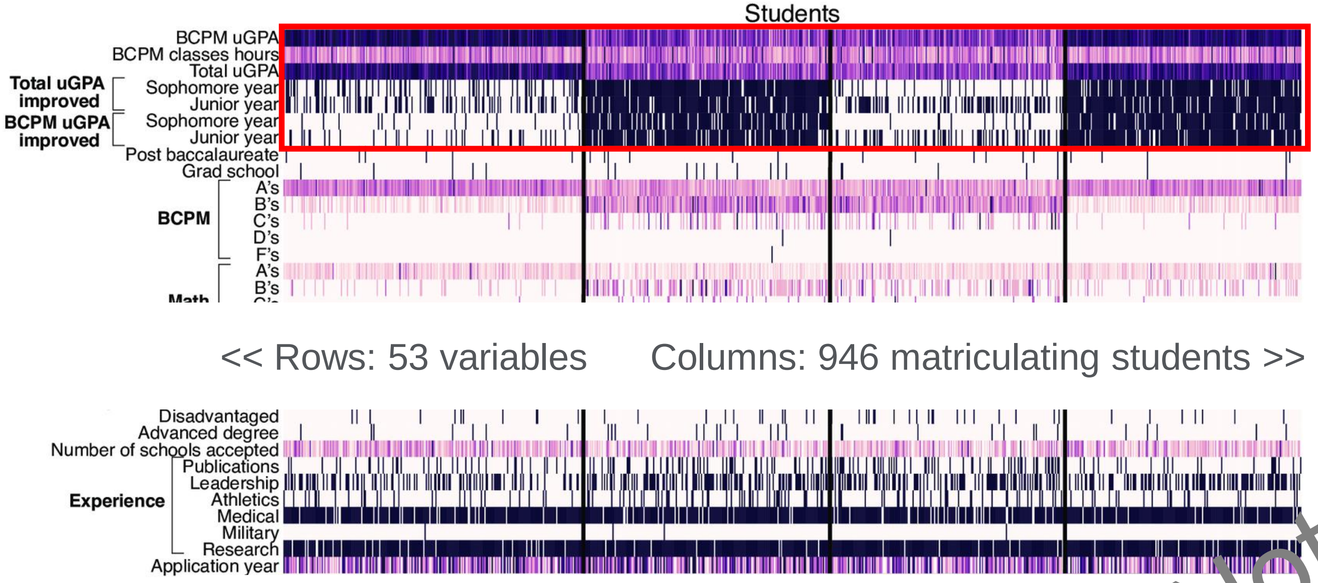
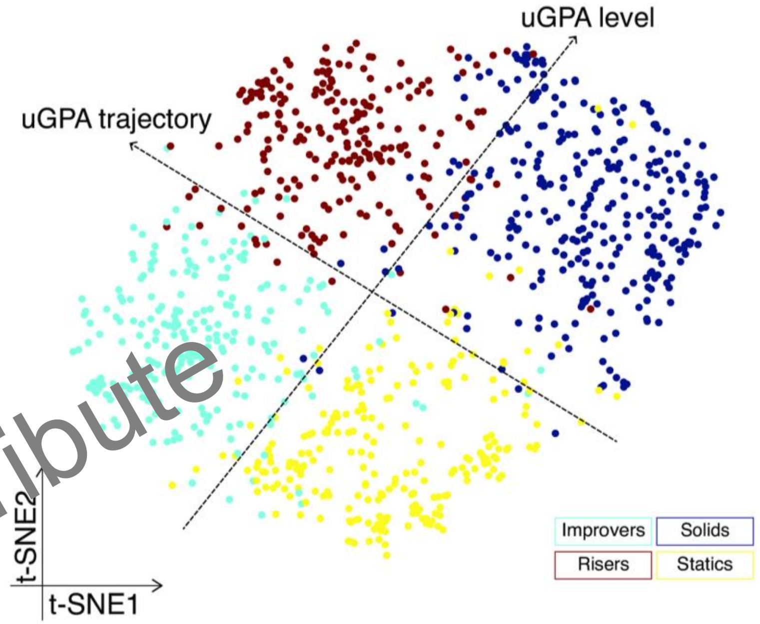
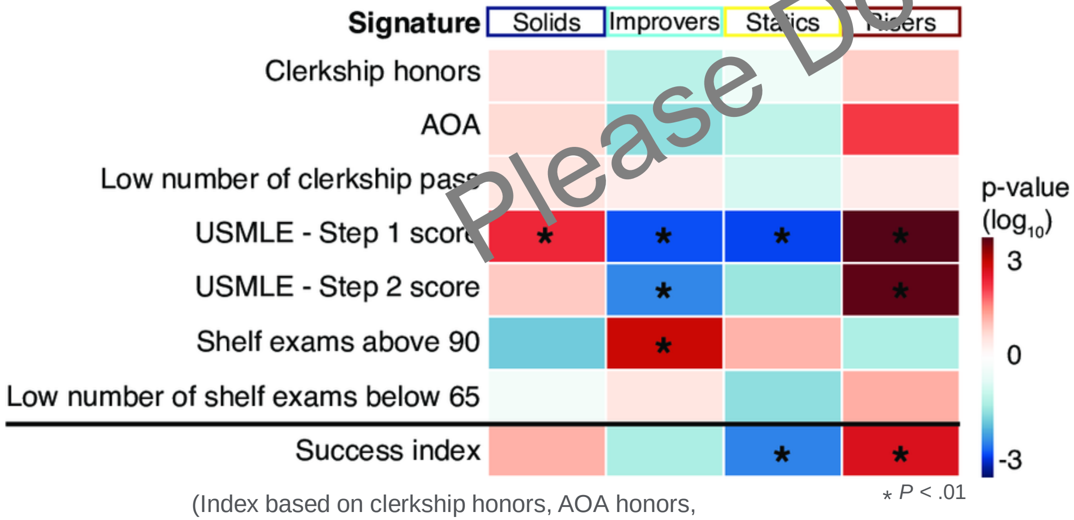
Adapted from: [Think Big: Learning Contexts, Algorithms, and Data Science]

Analytics: Learner Phenotypes







(Index based on clerkship honors, AOA honors, shelf scores, USMLE scores; 0=worst, 7=best)

- **Unsupervised k-means clustering revealed 4 latent "signatures" in applicant data**
  - Mostly distinguished by uGPA value and trajectory
- **Latent signatures improved prediction of "success" during training**
  - However, significant intra-signature variability
- **No apparent gender or socio-economic bias across signatures**
- **Limited to structured data and a narrow definition of "success"**

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Baron et al. Signatures of medical student applicants and academic success. PLOS One. 2020;15(1):e0227108.

@ jbrafel

Analytics: High Performance Computing

Jon Erlichman
@JonErlichman
Subscribe

Nvidia is now worth more than all of these companies combined:

AT&T
Boeing
Coca-Cola
Disney
FedEx
General Motors
IBM
McDonald's
Nike
Starbucks
UPS
Walmart

12:28 PM · 3/2/24 from Earth · **194K** Views

UltraViolet: NYU Langone's distributed-memory, high-performance computing cluster went live in July 2018. BigPurple is a hybrid cluster consisting of 157 compute nodes, 87 of which include graphics processing units (GPUs) for a total of 376 GPUs. BigPurple has 8 service nodes, 4 highly available login nodes, 4 data mover nodes, 8 high-memory nodes, and a 200Gb Infiniband-2 HDR interconnect.

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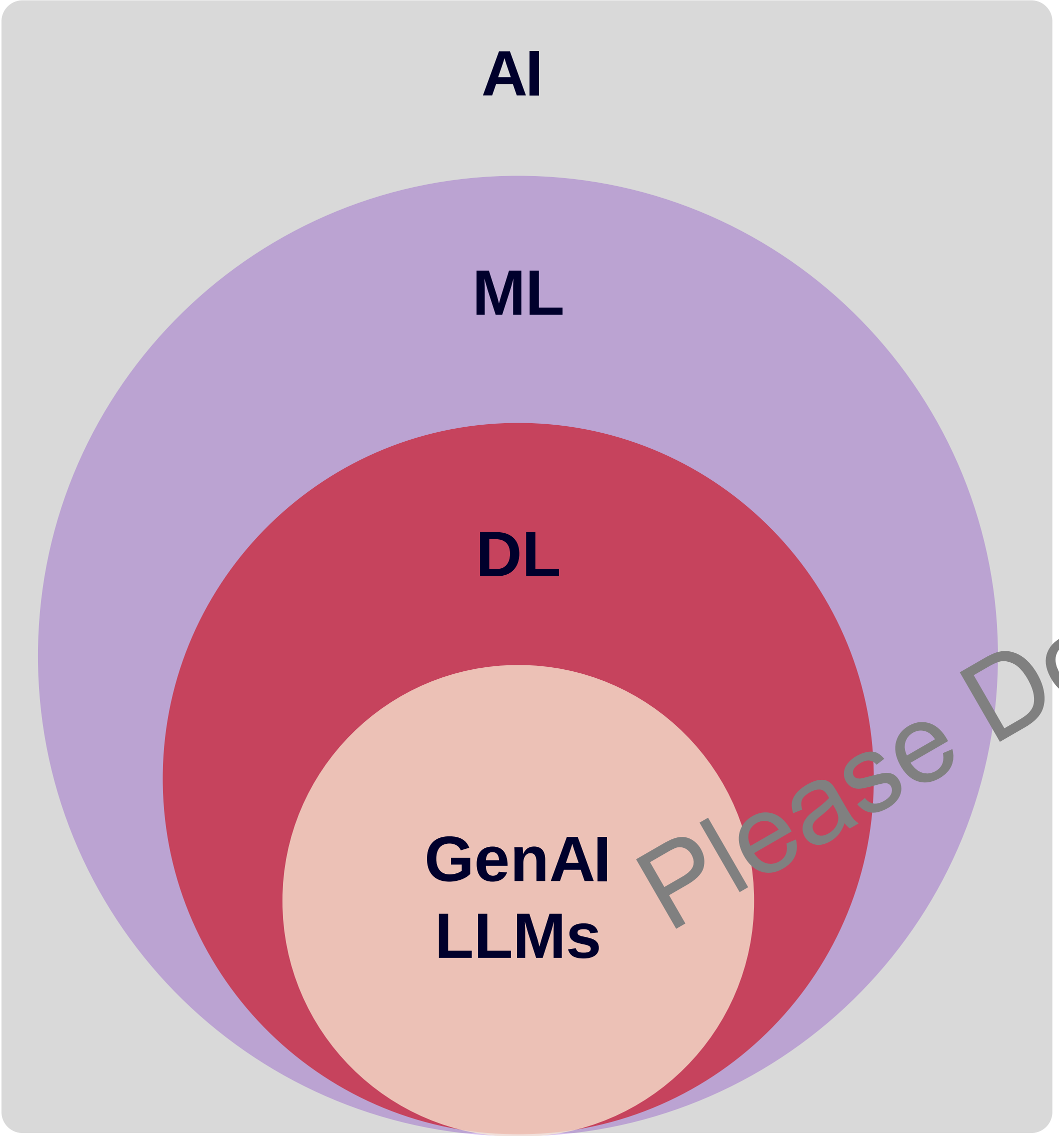
NYU Langone HPC and AI



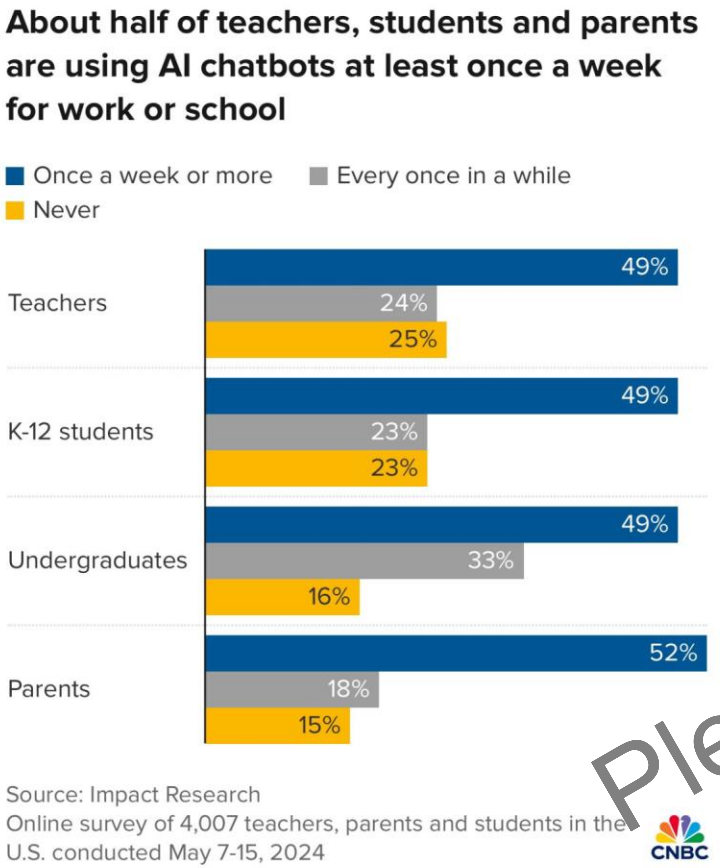
Artificial/Augmented Intelligence (AI)
Computer systems able to perform functions associated with human minds.

Machine Learning (ML)
Algorithms to detect patterns or make predictions. *Supervised, unsupervised, semi-supervised*, *reinforcement.*

Deep Learning (DL)
Subset of ML using *neural networks* (mimic neurons) in multiple layers.

Generative AI (GenAI)
Large Language Models (LLMs) use DL to create new data (text, images, video, music) similar to the training data. *Reinforcement learning with human feedback* (RLHF) used to improve chat responses.

Generative AI



User: Tell me about the potential side effects of this anti-bacterial that was prescribed for an infected finger

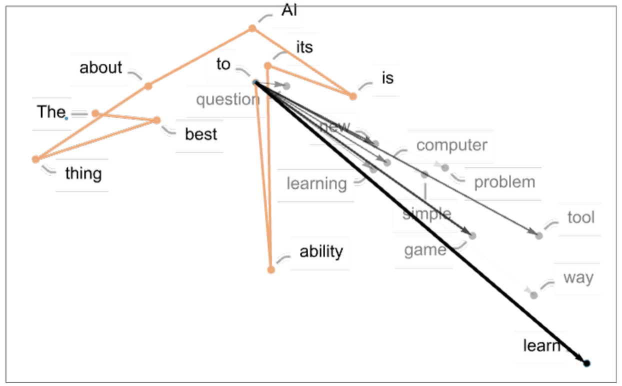
AI: The medication in the image you've shared is Cephalexin 500 mg capsules, which is indeed an antibiotic. Cephalexin is a cephalosporin antibiotic and is used to treat various bacterial infections.

Common side effects of cephalexin include: Diarrhea, Nausea…

@Scobleizer

The best thing about AI is its ability to

learn	4.5%
predict	3.5%
make	3.2%
understand	3.1%
do	2.9%



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@ jbrafel

Example GenAI at NYU: Curriculum Mapping

Lecture Description

In this lecture, you will learn about the mechanisms of liver injury and how that manifests in a variety of hepatic diseases. In addition to learning about the ways liver injury manifest, you will learn about the liver's amazing regenerative response and fibrosis that occurs with chronic injury. You will hear about the diseases that result in acute and chronic types of hepatocellular and cholestatic injury and learn the means to distinguish them. Perhaps most importantly, you will learn about drug-induced liver disease, which is quite common and potentially deadly. In all, this lecture will provide you an amazing framework for characterization of all manner of liver disease. Goal: Be able to describe the major histology of common types of hepatitis, identify the salient histological features of the etiology-specific hepatitis, and associate the histology with the clinical outcome.

+

ChatGPT Prompt

"Map this lecture to USMLE Content Area keywords and to MeSH terms:"

=

Result

USMLE Content Area Keywords:

- Liver injury mechanisms
- Hepatic diseases
- Liver regeneration
- Fibrosis
- Acute hepatocellular injury
- Chronic hepatocellular injury…

MeSH terms:

- Liver injuries
- Liver diseases
- Liver regeneration
- Liver cirrhosis
- Hepatitis…

NYU Langone Health

PI: Matt Polaniecki

Example GenAI at NYU: Key Points in Lecture Transcripts

Inbox | Calendar | MyData New! | QOD

Today's Events Nov 3, 2023

MyDay - AI

The lectures covered various topics related to cardiovascular health. Here are the key themes that emerged:

- Arrhythmia, specifically in regards to the cellular response and treatment options for this condition.
- Ischemia, stress testing, and anti-anginals, including the importance of pre-test probability and differential diagnosis in determining post-test probability.
- Clinical myocardial infarction, though information on the lecture is not provided.
- Peripheral vascular disease, focusing on the epidemiology, diagnosis, and pathogenesis of this condition.
- Personal protected time, which may refer to scheduled breaks or time off for healthcare professionals to address their own health and wellness.

Get ready to learn and grow! 🙌

Seminar: syncope (Arrhythmia)
9:00 am (1 hour 30 mins)
Organ Systems 1: Cardio, Pulmonary, & Kidney (2023-2024)

Ischemia, stress testing and anti-anginals (Skolnick)
SLH E
10:30 am (1 hour)
Organ Systems 1: Cardio, Pulmonary, & Kidney (2023-2024)

This will be a combination of lecture and application exercises. Assigned advanced reading: Lilly chapter on Ischemic Heart Disease Learning objectives: To understand the cellular response to ischemia and the steps in the ischemic cascade To understand the difference between anatomic and physiologic testing of coronary artery disease To understand the importance of pre-test probabilit...

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Example GenAI at NYU: "SMARTer" Student Goals

Medical Stu

Create a plan to
and advances of
-Weekly journal r
-Become familiar
-Read Cuccurullo

e fundamentals

achieve this goal

Suggested ways to accomplish this goal:

1. Join NYU Grossman School of Medicine's academic clubs, interest groups or student chapters of professional associations related to physiatry. This will provide opportunities to expand your knowledge, participate in organized discussions, and attend seminars or conferences.
2. Set up a weekly schedule to review journal articles related to physiatry. Utilize resources such as the American Journal of Physical Medicine & Rehabilitation and Archives of Physical Medicine and Rehabilitation. Staying up-to-date on recent research findings will enhance your understanding of the field.
3. Read and analyze the Cuccurullo textbook, "Physical Medicine and Rehabilitation Board Review." Cover one chapter or section each week, taking notes and discussing key points with classmates or mentors to ensure a thorough understanding of the material.
4. Participate in clinical rotations or observe physiatrists at Family Health Centers affiliated with NYU Langone Hospital – Brooklyn or other NYU-sponsored clinics. This hands-on experience will give you insight into the practice of physiatry while expanding your knowledge.
5. Attend physiatry-related webinars, conferences, and workshops offered by NYU Grossman School of Medicine, other medical schools, or professional associations. These opportunities will provide updates on the latest advances in the field, as well as the chance to network with professionals and fellow students with similar interests.

ChatGPT may produce inaccurate information about people, places, or facts

Save these suggestions as a note | Generate different suggestions | Rate this suggestion:

NYU Langone Health

Winkel AF, Chang LY, McGlone P, Gillespie C, Triola M. SMARTer goalsetting: a pilot innovation for coaches during the transition to residency. Acad Med. 2023.

AMA

Support: AMA ChangeMedEd

HOW

Precision Education Interventions

NYU Langone Health

Interventions: Theoretical Foundations and Digital Tools

PRECISION INTERVENTIONS

Personalized Coaching

Coaching on individual practice habits and AI-assessed clinical reasoning documentation quality

THEORETICAL FOUNDATIONS

Master Adaptive Learner Theory

Planning & Learning: panel management documentation didactics

Assessing: review metrics with coach

Adjusting: action plan

DIGITAL TOOLS

Dashboard Audit & Feedback

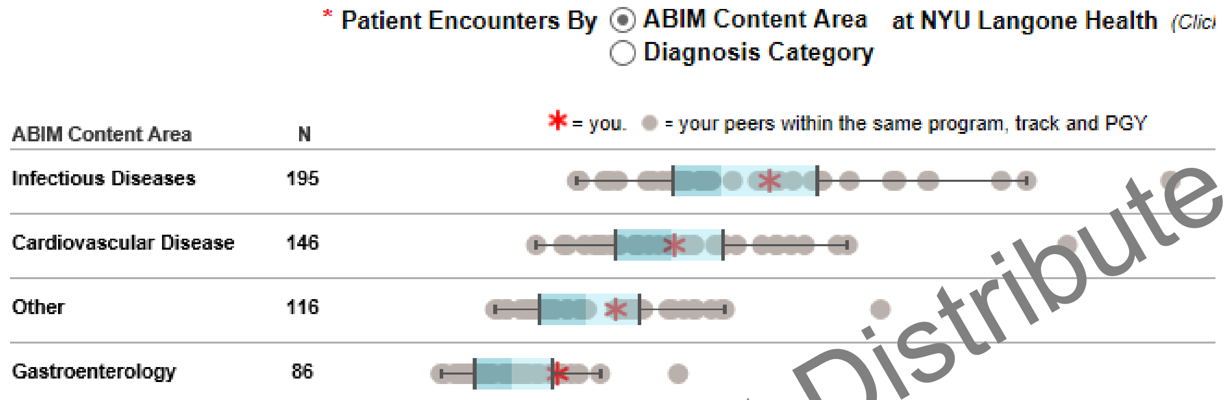
Timeliness: near real-time

Low cognitive load: simple presentation

Drake et al. A Theoretical Foundation to Inform the Implementation of Precision Education and Assessment. *Acad Med*. 2024.

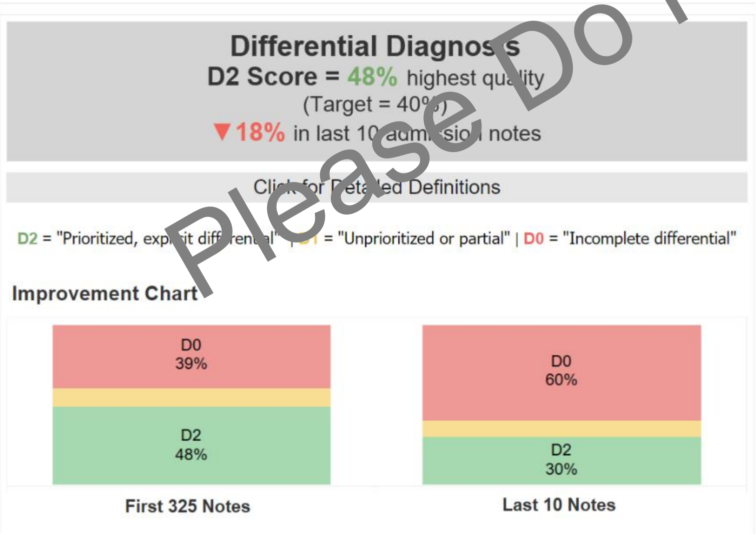
Interventions: Dashboards as Digital Tools

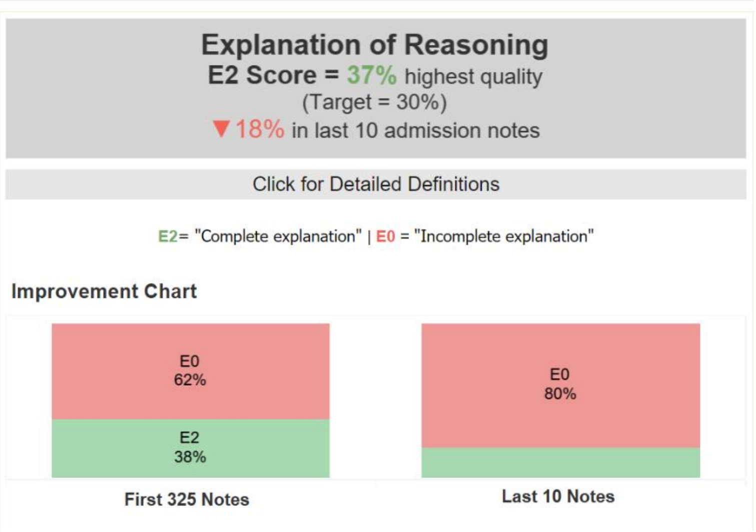
Diagnostic Exposure



- ✓ Criterion benchmarks (both static and improvement)
- ✓ Direct link to EHR encounter
- ✓ Coaches / PDs can view outliers
- ✓ Organized by board domains

Clinical Reasoning Documentation





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NBME

Support: Stemmler Fund

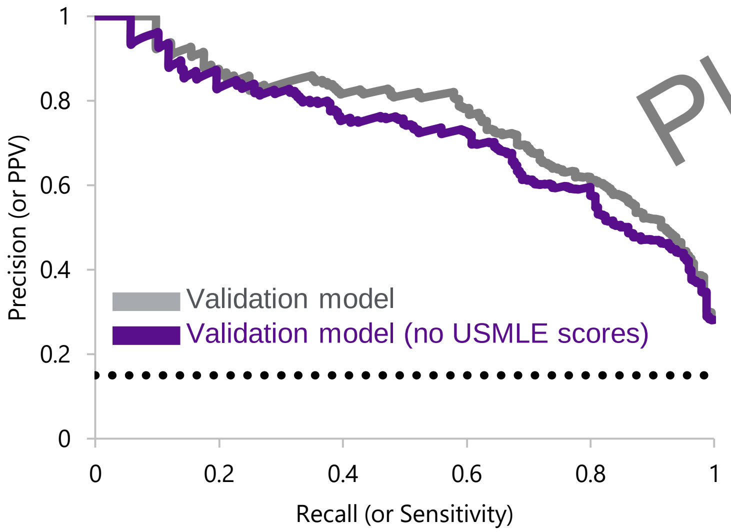
X @ jbrafel

Interventions: Dashboards as Digital Tools (AI Holistic Review)

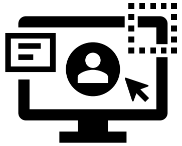
Training Data
ERAS: 2018, 2019, & 2020 cycles
8,243 applicants
1,235 interview invites

Cleaning & Feature Extraction
>640 ERAS fields ➡ 61 features
Normalized, missing data imputed
NLP of narrative components

Model Selection & Tuning
80% of dataset (Training Data)
LR, RF, LightGBM, XGBoost



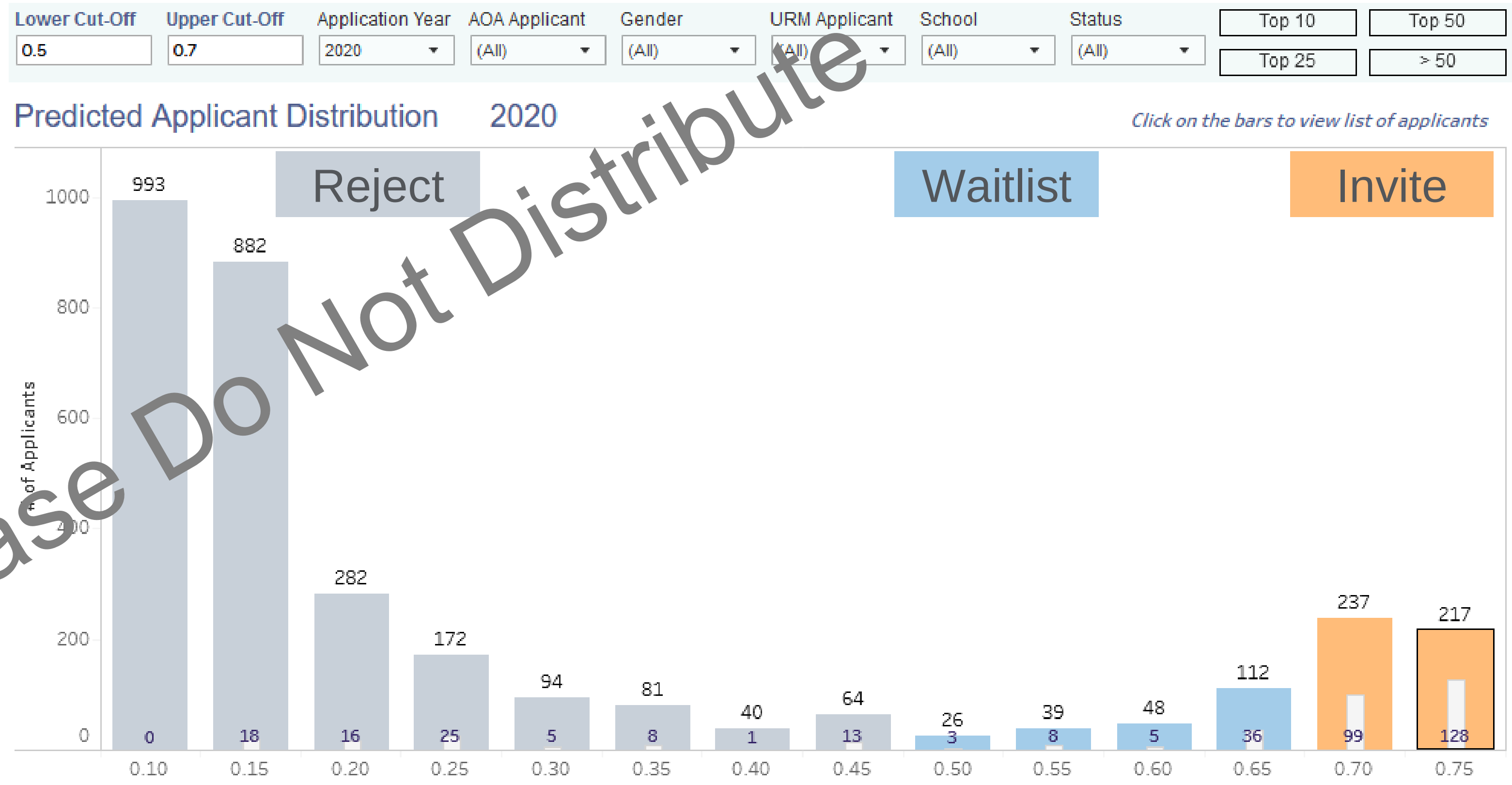
Decision Support Tool



Invite

Not invite

"Diamonds in the rough"?



Reject Predicted

Invite Predicted

Burk-Rafel et al. *Acad Med*. 2021;96(11S):S54-S61.
Mahtani et al. *Acad Med*. 2023;98(9):1018-1021.

Interventions: Theoretical Foundations and Digital Tools

PRECISION INTERVENTIONS	THEORETICAL FOUNDATIONS	DIGITAL TOOLS
Personalized Coaching Coaching on individual practice habits and AI-assessed clinical reasoning documentation quality	**Master Adaptive Learner Theory** *Planning & Learning*: panel management documentation didactics *Assessing*: review metrics with coach *Adjusting*: action plan	**Dashboard Audit & Feedback** *Timeliness*: near real-time *Low cognitive load*: simple presentation
Targeted Educational Resources Educational resources delivered to care team based on recent patient diagnoses	**Self-Determination Theory** *Autonomy*: self-select resource when wanted *Competence*: multiple-choice questions curated for appropriate difficulty *Relatedness*: shared learning with team	**Nudge Strategy** *Structuring defaults*: pre-set options for content review *Redefining norms*: sent to team as “usual” care *Salience*: tied to recent patient diagnosis

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Drake et al. A Theoretical Foundation to Inform the Implementation of Precision Education and Assessment. *Acad Med*. 2024.

X @ jbrafel

Interventions: “Nudges” as Digital Tools

Admission Monday 6pm; nudge sent Tuesday 7am to trainee & attending

Yesterday you admitted a **44 y.o. woman with cirrhosis and alcoholic hepatitis.** This was **your 3rd admission** of this type at NYU Langone (vs. median 2 for peers) and your **H&P demonstrated high-quality clinical reasoning** – great job! However, your note **lacked supporting evidence** for your leading diagnosis. Below are some AI-generated **educational resources** you might find useful in caring for this patient.

CoreIM
- Alcohol-Associated Hepatitis: 5 Pearls Segment

Timely, relevant

Curbsiders
- Cirrhosis: Initial Evaluation and Management
- Cirrhosis: Medications, decompensation, complications
- NephMadness: Hepatorenal Syndrome vs AKI

UpToDate
- Alcoholic hepatitis: Clinical manifestations and diagnosis
- Pathogenesis of alcohol-associated liver disease

Theory informed

Cue	Behavior
Messenger	Influenced by who communicates to us
Incentives	Predictable responses (e.g. loss avoidance)
Norms	Influenced by what others do
Defaults	“Go with the flow” of pre-set options
Salience	Attention goes to novel, relevant things
Priming	Influenced by sub-conscious cues
Affect	Emotional associations shape actions
Commitments	Seek to keep public promises and reciprocate
Ego	Act to feel better about ourselves

Yoong et al. *Implementation Science*. 2020;15(1):50.

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NYU Grossman School of Medicine — Institute for Innovations in Medical Education

For: [redacted]

Below are suggested personalized learning resources based on recent notes you wrote in Epic. These recommendations were automatically generated by an **AI education system developed at NYU Grossman.**

View More >

Fun!

Recent Cases

42 YEAR-OLD FEMALE WITH A DIAGNOSIS OF ACUTE PANCREATITIS, UNSPECIFIED COMPLICATION STATUS, UNSPECIFIED PANCREATITIS TYPE

Amboss: *Acute pancreatitis*

Open Amboss → | Related Q-Bank Questions →

Suggested Review Article
Acute Pancreatitis: A Review. JAMA. Jan 2021. — Read now

- "Several scoring systems, such as BISAP and APACHE II, have good predictive capabilities for disease severity and mortality in acute pancreatitis."
- "Early and aggressive fluid resuscitation and early enteral nutrition are associated with lower rates of mortality and infectious complications."
- "Prompt diagnosis and stratification of severity influence proper management in acute pancreatitis."

Suggested Randomized Controlled Trial Article
Aggressive or Moderate Fluid Resuscitation in Acute Pancreatitis. N Engl J Med. Sep 2022. — Read now

- **Implications:** The study suggests that aggressive fluid resuscitation in acute pancreatitis may increase the risk of fluid overload without improving clinical outcomes.
- **Safety Concerns:** The higher incidence of fluid overload in the aggressive resuscitation group raises safety concerns, which warrants further investigation into safe fluid management strategies in acute pancreatitis.
- **Future Directions:** Research should focus on identifying effective, safe fluid management strategies in acute pancreatitis, potentially including individualized fluid resuscitation based on patient response and risk factors.

Institute for Innovations in Medical Education
EducationIT@nyulangone.org | med.nyu.edu

FUTURE

—

Precision Education

NYU Langone Health

Concluding Thoughts: Precision Education

Training programs are the "tip of the spear" for curtailing unwanted variability in clinical practice patterns – and solidifying excellence in our health professions workforce

Precision education provides an organizing framework for providing **outcome-informed education to the right trainee at the right time**

Inputs and outcomes should span **multiple sources,** with novel measures based on **clinical care data augmenting** traditional human rater-based assessments

Data is the new currency of medical education. **Invest!**

Concluding Thoughts: Precision Education

Find common ground (e.g. dashboards) for **aligning educational and clinical informatics** – linking these worlds is essential!

Organizations must develop **analytic maturity**, moving from descriptive to prescriptive approaches that apply **high-performance computing** and **AI**

Grounding **precision interventions** in **strong theory** and **effective digital tools** can improve the likelihood of success

Engage **learners in co-production** – they are usually the smartest people in the room!

Concluding Thoughts: MedEd and AI

Your **students and residents are using these tools.** AI tools are ubiquitous – so much so that people do not realize they are using them

Create a policy for responsible use and provide a HIPAA-secure instance

Be transparent about how you are using AI and with which learner data

Be growth-minded: AI **unlocks incredible new possibilities** but carries **new challenges**

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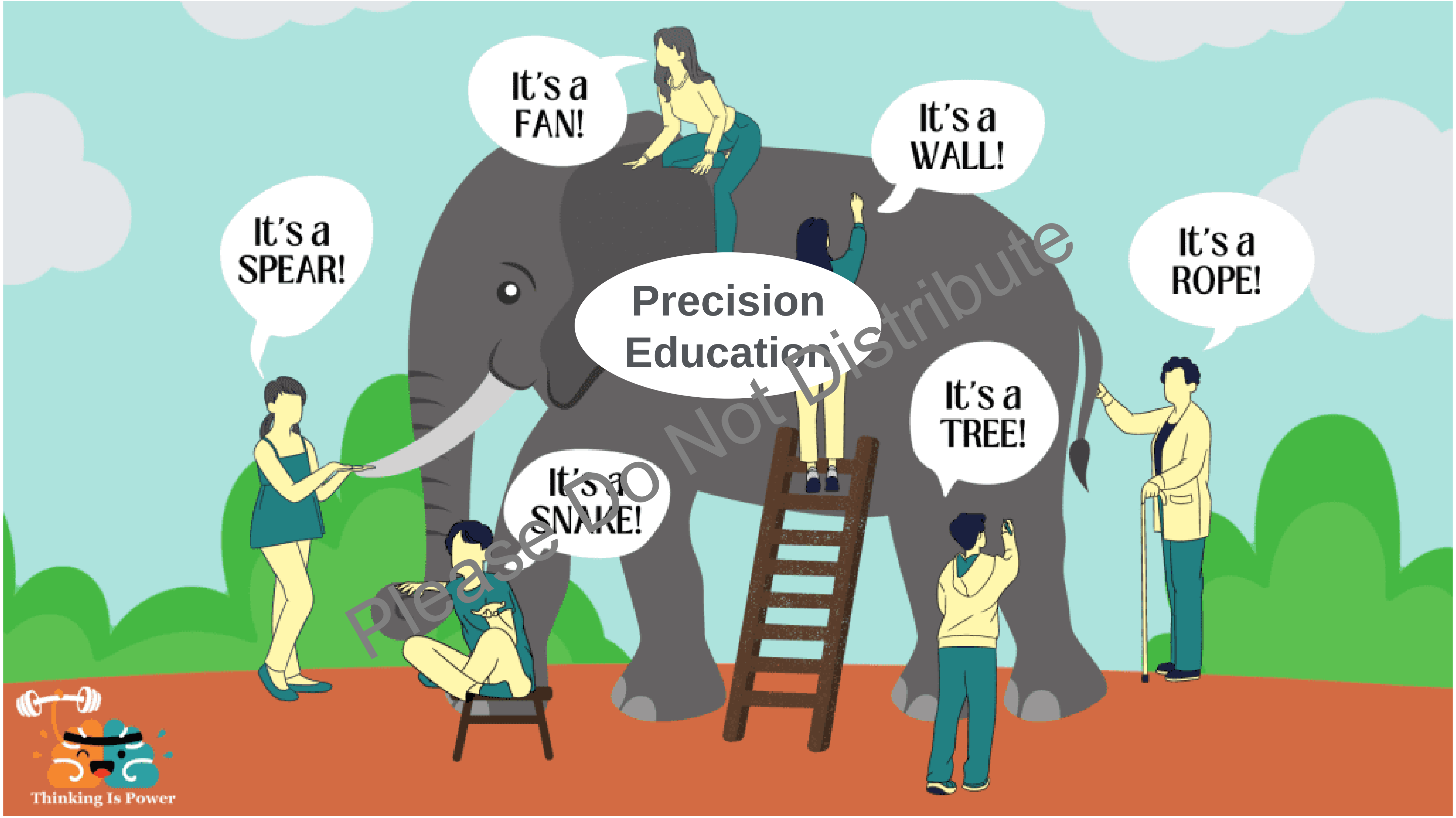
Unanswered Questions: MedEd and AI

- What will be the "**uniquely human**" behaviors of physicians in practice 10 years from now?
- How do we **train students for a future** that will include AI-driven documentation or AI-supported clinical reasoning?
- What **skills should be taught differently** or only via AI?
- If AI can easily pass high-stakes exams, how **should we think differently about assessing** our learners?
- What does **authorship and plagiarism** mean when using AI?
- **Etiquette**: when is it appropriate to use these tools?

NYU Langone Health

Pearce J, Chiavaroli N. Rethinking assessment in response to generative artificial intelligence. Med Educ. 2023 Oct;57(10):889-891.

Links, tutorials, examples available at: **ai.iime.cloud**


It's a FAN!
It's a WALL!
It's a SPEAR!
Precision Education
It's a ROPE!
It's a TREE!
It's a SNAKE!
Thinking Is Power

The Next Era of Assessment: Advancing Precision Education for Learners to Ensure High-Quality, Equitable Care for Patients (*Academic Medicine* supplement out late March)

Precision Education

- The Next Era of Assessment: Can Ensuring High-Quality, Equitable Patient Care Be the Defining Characteristic? (Schumacher et al.)
- Precision Education: The Future of Lifelong Learning in Medicine (Desai et al.)
- Trainees' Perspectives on the Next Era of Assessment and Precision Education (Marcotte et al.)
- Precision Education and Equity: A Participatory Framework to Advance Equitable Assessment (Sukhera)

Implementation Frameworks

- A Theoretical Foundation to Inform the Implementation of Precision Education and Assessment (Drake et al.)
- Learner Assessment and Program Evaluation: Supporting Precision Education (Richardson et al.)
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