Advancing Critical Care through Data Science

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Critical Care Congress
#CCC49

Disclosure/Conflict of Interest

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https://github.com/nsanchezpinto/SCCM2020

Learning Objectives

- Discuss **6 things to consider** when implementing **data-driven systems in critical care**
- Propose a **simple framework to build successful data-driven systems** to improve care

NOTE: This discussion is focused on **supervised learning algorithms** (AKA **predictive analytics** or **clinical prediction models**)

6 things to consider when implementing data-driven systems in critical care

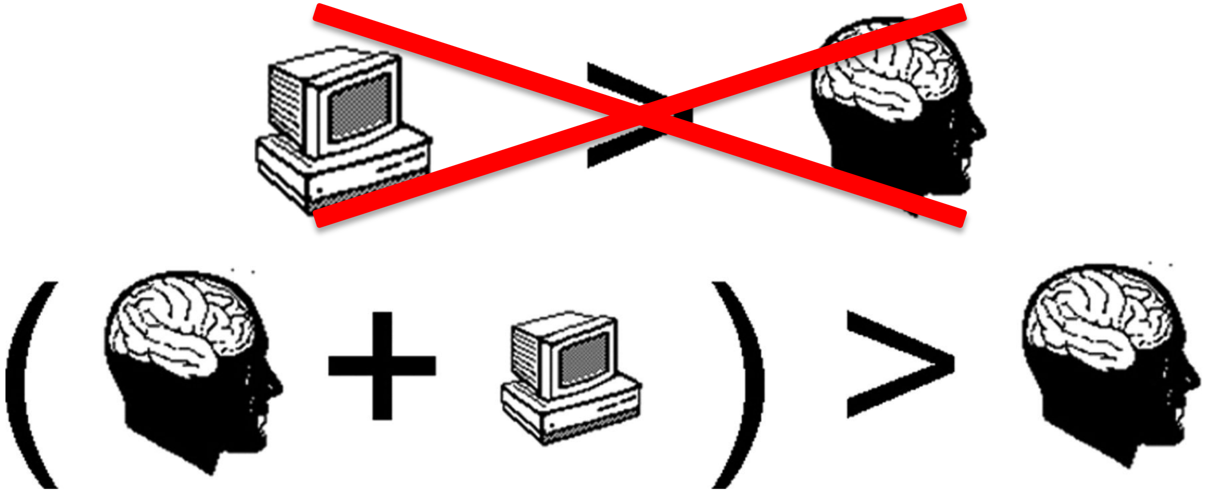
1. The **“fundamental theorem”** of biomedical informatics still applies

Viewpoint Paper ■

A “Fundamental Theorem” of Biomedical Informatics

Charles P. Friedman, PhD

J Am Med Inform Assoc. 2009;16:169–170. DOI 10.1197/jamia.M3092.



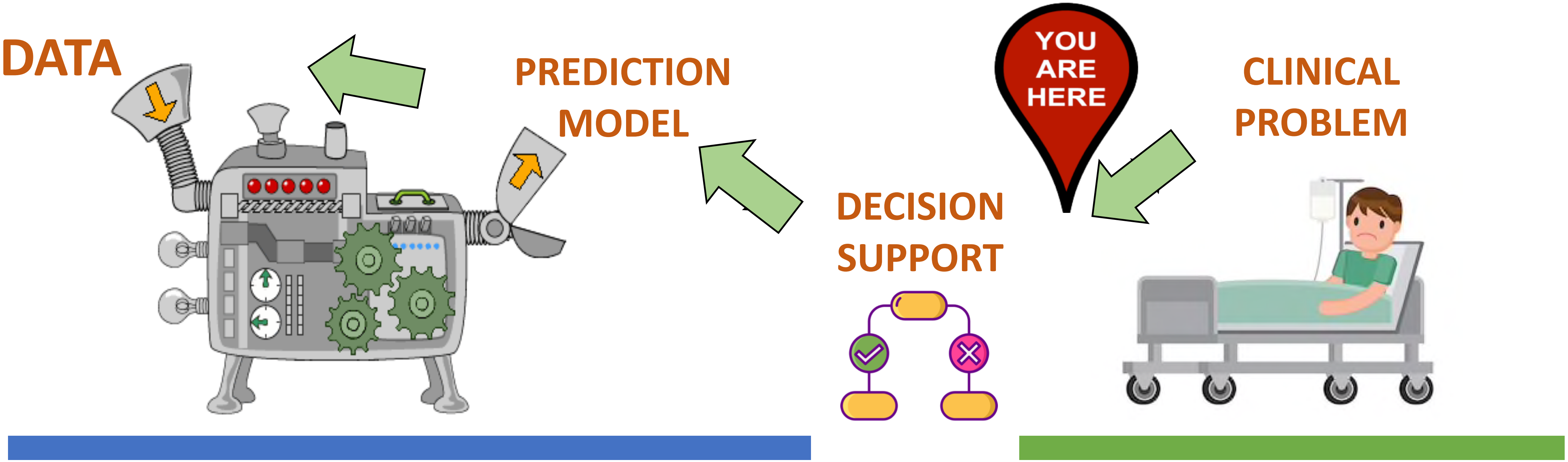
“The complexity of modern medicine exceeds the inherent limitations of the unaided human mind”

- David Eddy, 1990

Corollaries:

1. It’s **more about people** than technology
2. The technology **must offer something** that the person does not already know or have
3. Its success depends on an **effective interaction between person and technology**

2. It’s important to **understand the clinical problem**, and then work backwards



Inside a computer
(maybe in Silicon Valley)

In the real world

2. It's important to **understand the clinical problem**, and then work backwards

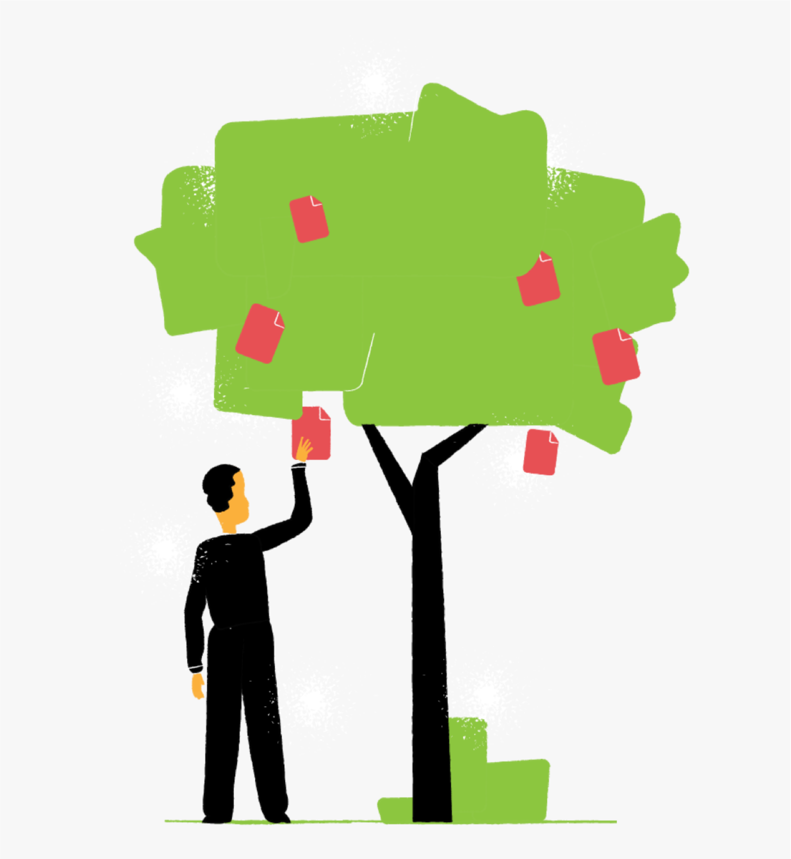
QUESTIONS WE MAY CONSIDER:

- What are we trying to solve? → Event is frequent enough? Easy to identify electronically?
- How can we solve it? → Another alert? A stratification? Is it actionable? Is it useful?
- Who needs the decision support? → Physician? Nurse? RT? Patient?
- Where in the workflow does this make sense? → Make it easy to do the right thing
- What are the possible unintended consequences? → Consider FMEA

2. It's important to **understand the clinical problem**, and then work backwards

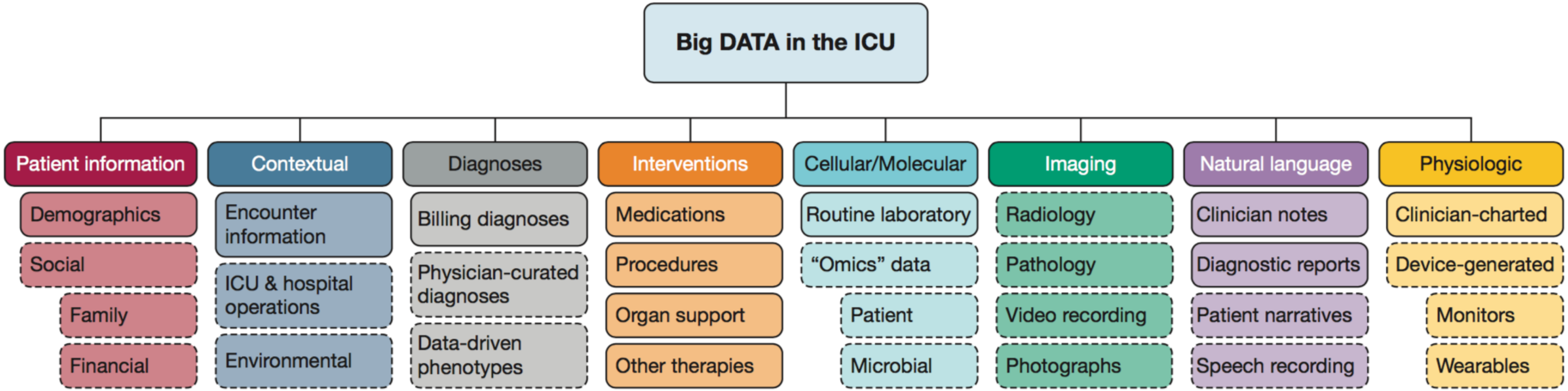
- Plenty of "**low-hanging fruit**" ICU problems:
  - ✓ Reduce X-rays and lab tests
  - ✓ Shorten empiric antibiotics

- **Hard, non-specific problems** (e.g. sepsis, readmissions) are important but can be frustrating



3. The prediction model will only be **as good as the data** (Garbage In = Garbage Out)

- Consider the type, amount, and quality of data available:



[Contemporary Reviews in Critical Care Medicine] CHEST

Big Data and Data Science in Critical Care

L. Nelson Sanchez-Pinto, MD; Yuan Luo, PhD; and Matthew M. Churpek, MD, PhD

3. The prediction model will only be **as good as the data** (Garbage In = Garbage Out)

- **Data quality** + **adequacy** checks:
  - ✓ Conformance
  - ✓ Completeness
  - ✓ Plausibility
  - ✓ Relevancy
  - ✓ Timeliness

- “Clean” the data but **be pragmatic**!
  Models need to work in real life

4. When choosing an ML/AI algorithms, **interpretability is still important** (…as long as the model is accurate)

VIEWPOINT

Clinical Decision Support in the Era of Artificial Intelligence

JAMA December 4, 2018 Volume 320, Number 21

"**Black boxes are unacceptable**: A decision support system requires **transparency** so that users

Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead

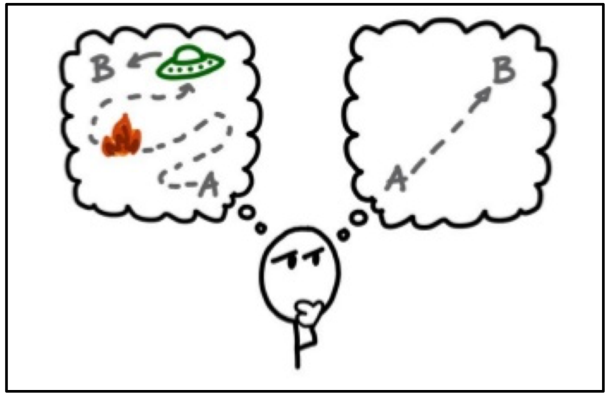
Nature Machine Intelligence 1, 206–215(2019)

"**Trying to *explain* black box** models, rather than creating models that are *interpretable* in the first place, **is likely to perpetuate bad practices** and can potentially cause catastrophic harm"

4. When choosing an ML/AI algorithms, **interpretability is still important** (…as long as the model is accurate)

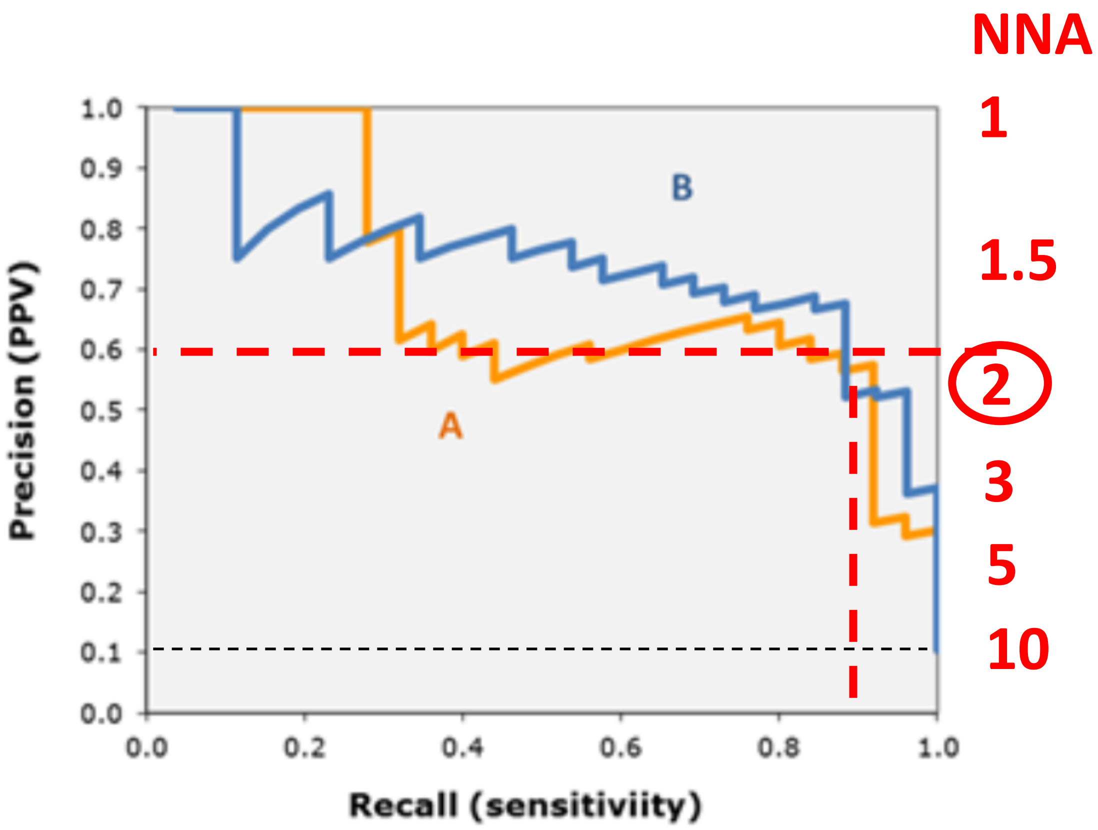
Consider:

- **Rashomon Effect**: Multiplicity of good models
- **Occam's Razor**: Balance simplicity and accuracy



5. Use **performance measures for the real world** (and validate them!)

- **AUCs are not always useful** or reflect real-world use cases
- **Precision-Recall Curves** can be very useful **for infrequent events**
- Consider the "**number needed to alert**" (NNA) = 1/PPV



5. Use **performance measures for the real world** (and validate them!)

Crystal Balls and Magic Eight Balls: The Art of Developing and Implementing Automated Algorithms in Acute Care Pediatrics*

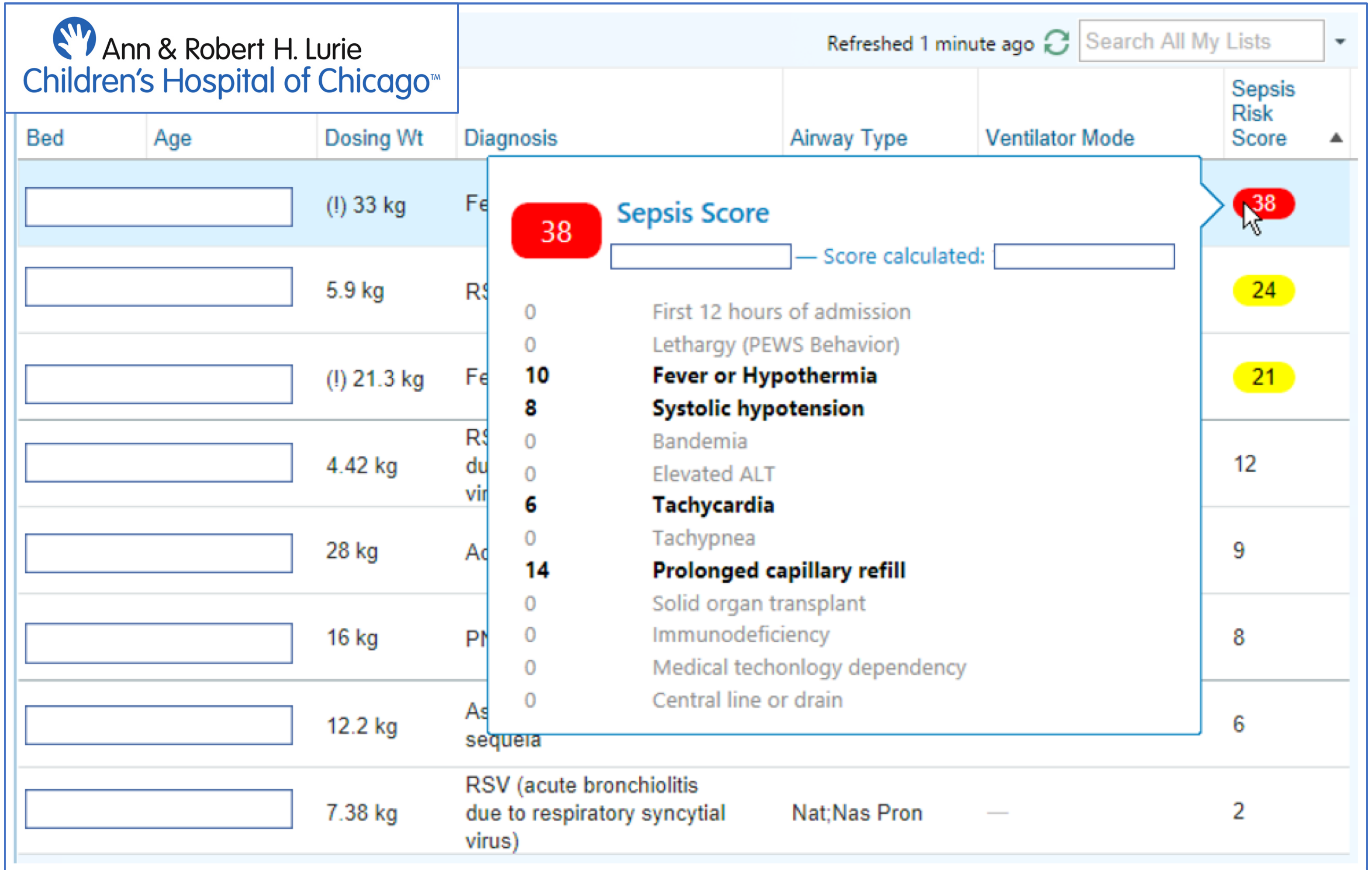
Pediatric Critical Care Medicine December 2019 • Volume 20 • Number 12

NNA at an Acceptable Sensitivity	Examples of Alert Workflows and Interventions to Consider at the Different NNA Performance Levels
< 5	Tier 1 Confirmatory testing, if available Escalation to higher level of care, if needed Early therapeutic intervention if warranted
5 to 10	Tier 2 Bedside evaluation and escalation to tier 1 if needed Training centered around individual at-risk patients Just-in-time team-based simulations
> 10	Tier 3 Increased team situational awareness through structured communication tools (3), standardized handoffs, and huddles More frequent assessments and escalation to tier 1 or 2 as needed

NNA = number needed to alert.

The NNA cutoffs, sensitivity level, and interventions used here are only illustrative and will change based on the clinical problem and resources available.

5. Use **performance measures for the real world** (and validate them!)



NNA ~ 8
= "Alert" = huddle

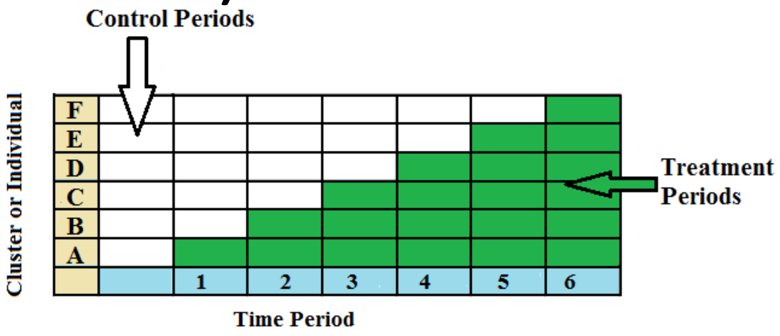
NNA ~ 15
= "Aware" = no alert

6. Finally: **implement, study, and iterate** (the last mile is the most important!)

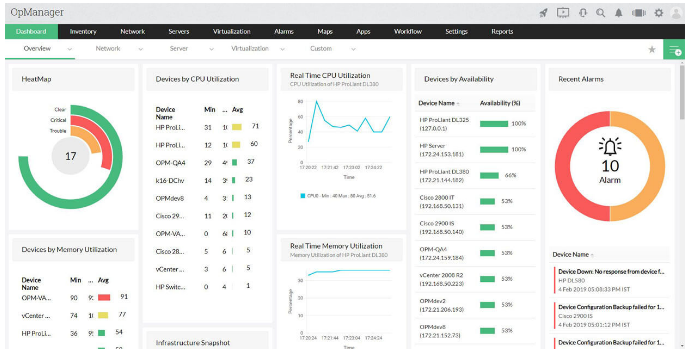
➢ Decision support implementations are **more about people than technology**

➢ Many ways to **study effectiveness** (but pick one!):

- Single-arm intervention study
- Cluster RCT
- QI, control charts

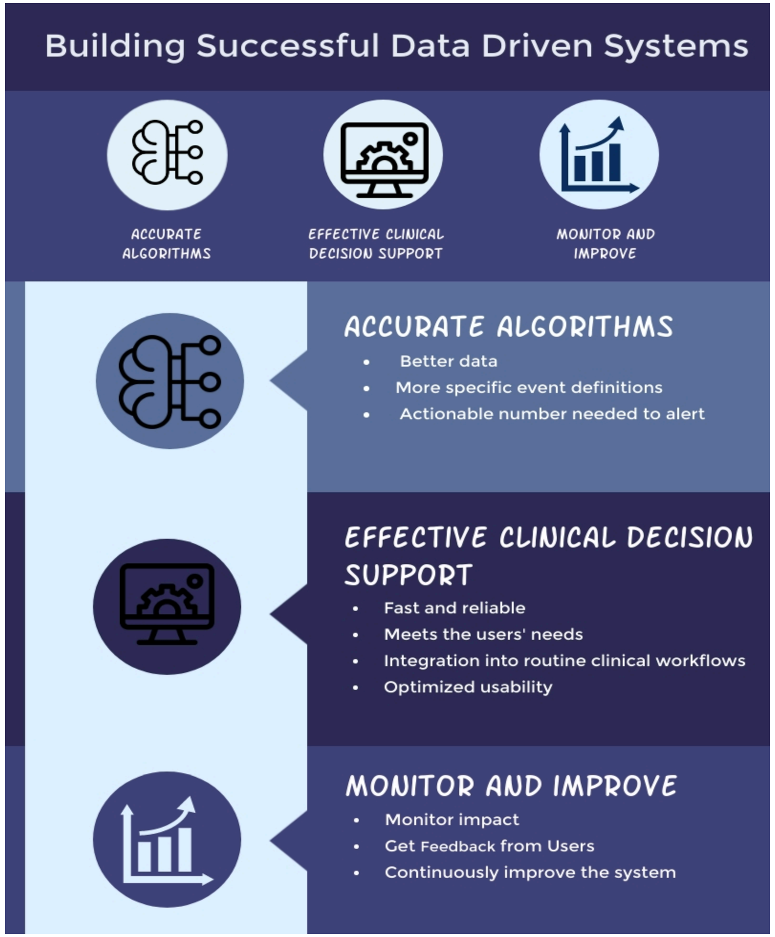


➢ Monitor **model performance** and **clinician acceptability**/action



➢ If needed: **rinse and repeat**

A simple framework to build successful data-driven systems in critical care



(1) Develop and validate **accurate models/algorithms** by using **better data**, use **actionable thresholds** for **specific, modifiable events**

(2) Design **effective decision support systems** that meet the **clinician's needs**, integrate into **workflow**

(3) **Study effectiveness**, **monitor performance**, get **feedback**, **improve** system

Dewan M, Sanchez-Pinto LN. *Crystal Balls and Magic Eight Balls: The Art of Developing and Implementing Automated Algorithms in Acute Care Pediatrics.* Pediatric Critical Care Medicine. 2019 Dec 1;20(12):1197-9.

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