Big Data and the Smallest People: Leveraging Informatics and Machine Learning to Improve Your Clinical and Research Practice

Kristyn Beam, MD MPH
Ameena Husain, DO
Brynne Sullivan, MD MSCR
Zachary Vesoulis, MD MSCI

PAS 2023

@SullivanBrynne
@VesoulisLab

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(*please note symbol in upper right*)

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Kristyn Beam, Ameena Husain, Brynne Sullivan
Have documented no financial relationships to disclose or Conflicts of Interest (COIs) to resolve.

Zachary Vesoulis
Has documented consulting and grant support from Medtronic, grant support from Edwards LifeSciences.

All authors have
Has documented this presentation ***will not*** involve discussion of unapproved or off-label, experimental or investigational use.

Introductions

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Kristyn Beam, MD MPH
Instructor in Pediatrics
Beth Israel Deaconess
Boston, MA

Beth Israel Deaconess Medical Center
HARVARD MEDICAL SCHOOL TEACHING HOSPITAL

Ameena Husain, DO
Assistant Professor
University of Utah
Salt Lake City, UT

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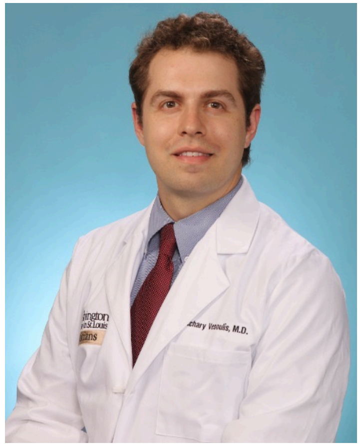
Brynne Sullivan, MD MSCR
Assistant Professor
University of Virginia
Charlottesville, VA

UVA Children's



Zachary Vesoulis, MD MSCI
Assistant Professor
Washington University
St. Louis, MO

Children's

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Workshop outline/schedule

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- 3 didactic sessions (15 min each)
  - EHR-integrated tools: Ameena Husain
  - Overview of Machine Learning Tools: Kristyn Beam
  - Data analytics: Brynne Sullivan
- Live demonstration sessions
  - Data handling, visualization, and statistics
  - Sample cases
- Wrap-up and Q&A

Before we start

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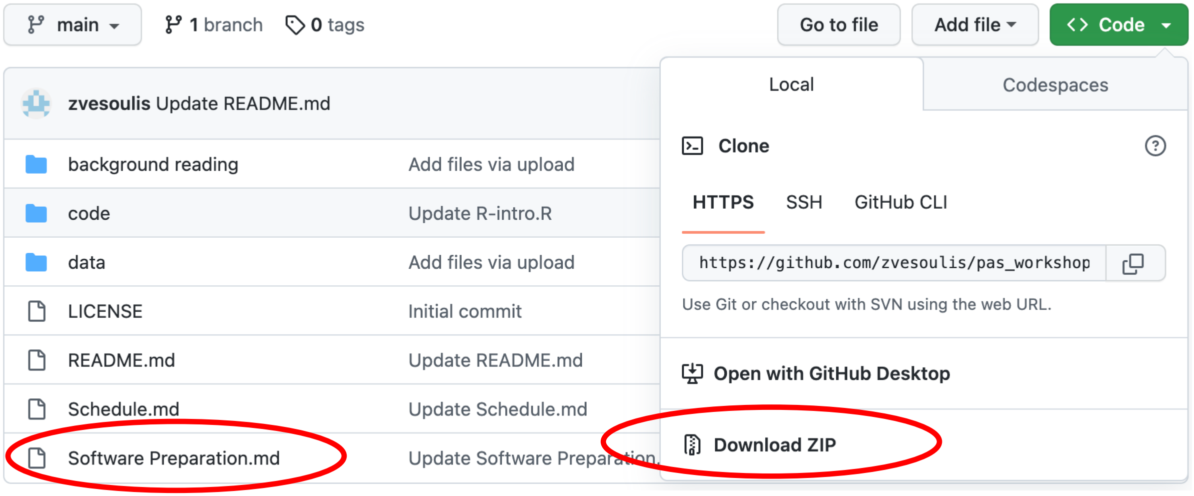
- As noted in the handout, you will need a charged laptop computer and downloaded/installed software and data to actively participate in the live demo.
- If you haven't already downloaded this material, please visit https://github.com/zvesoulis/pas_workshop2023 and download the package.
- During the limited session length, we won't have time to troubleshoot problems during the session.



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EHR-Integrated Tools

Ameena Husain
University of Utah

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Outline

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1) Overview of data structure
   i. Examples in EHR Epic

2) EHR-Integrated reporting

3) Challenges

4) Additional learning opportunities

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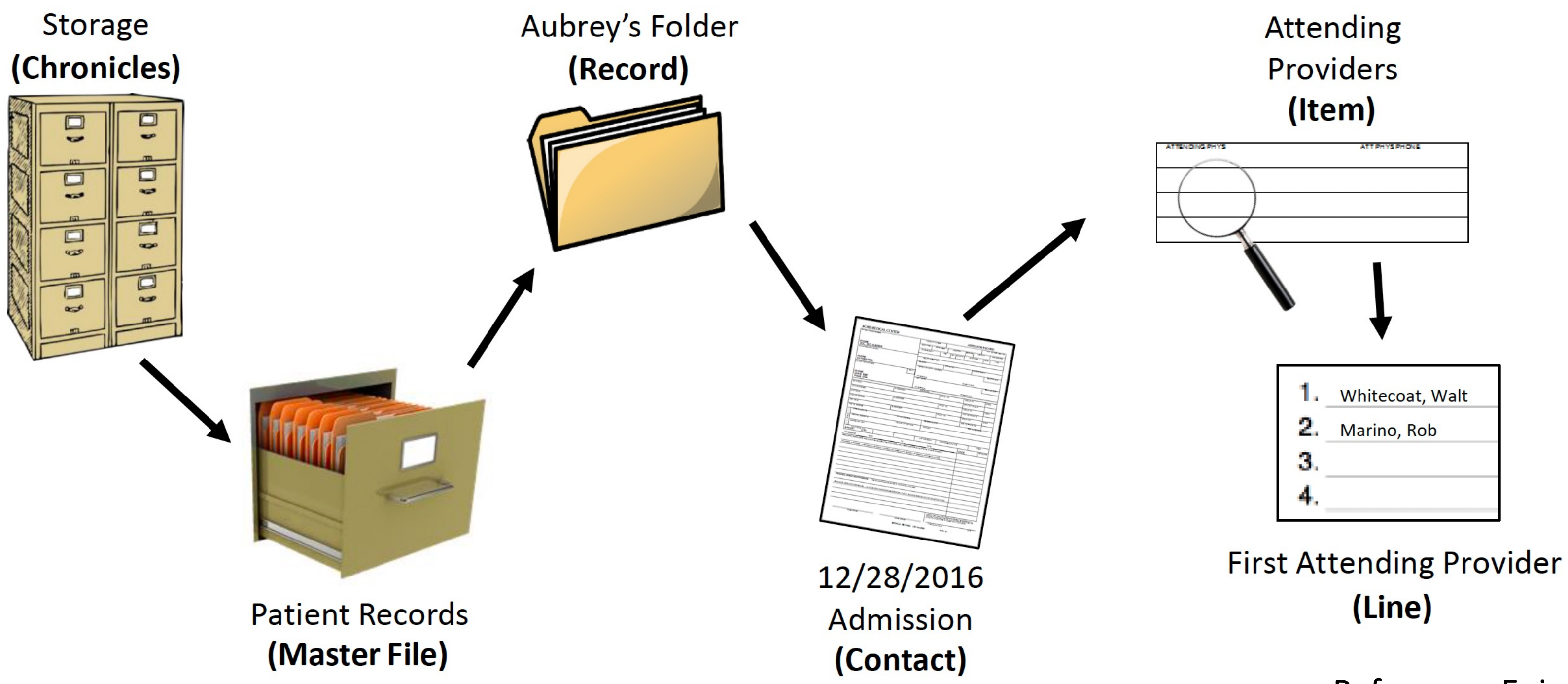
Data Structure – Epic

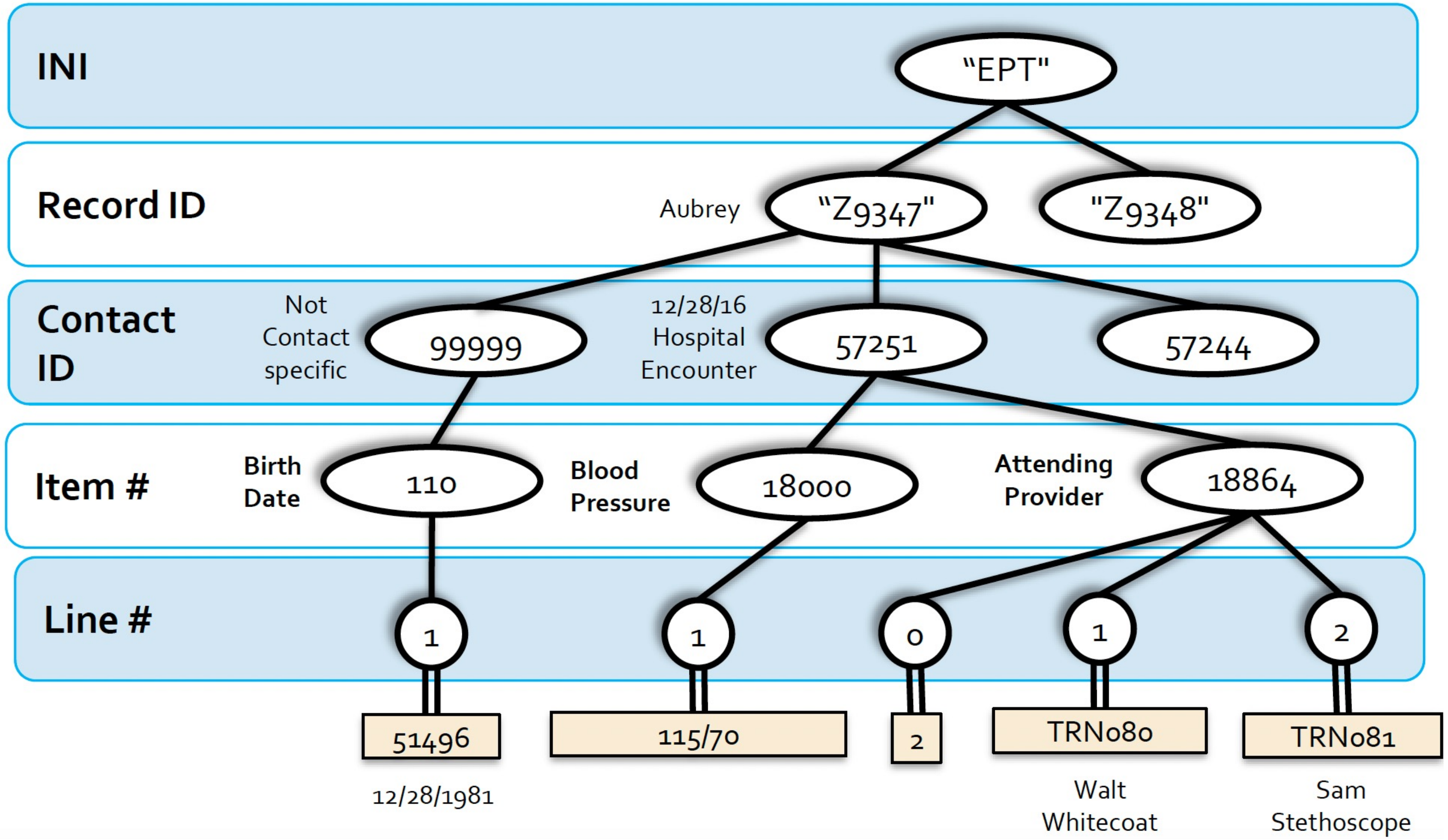
Don’t Share



Reference: Epic

Data Structure – Epic

Don't Share



Reference: Epic

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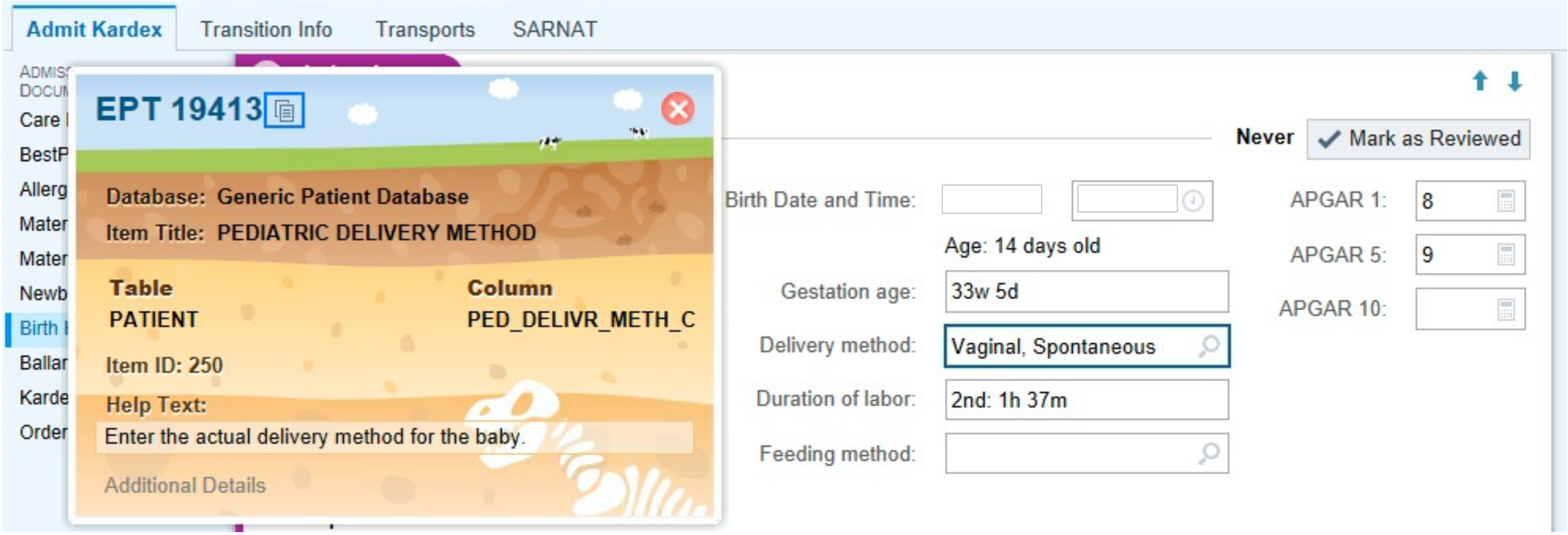
Data Structure – Epic

Don't Share

Record Viewer (item level view of data within hyperspace)
Use "CTRL-click' function within fields to find data point information



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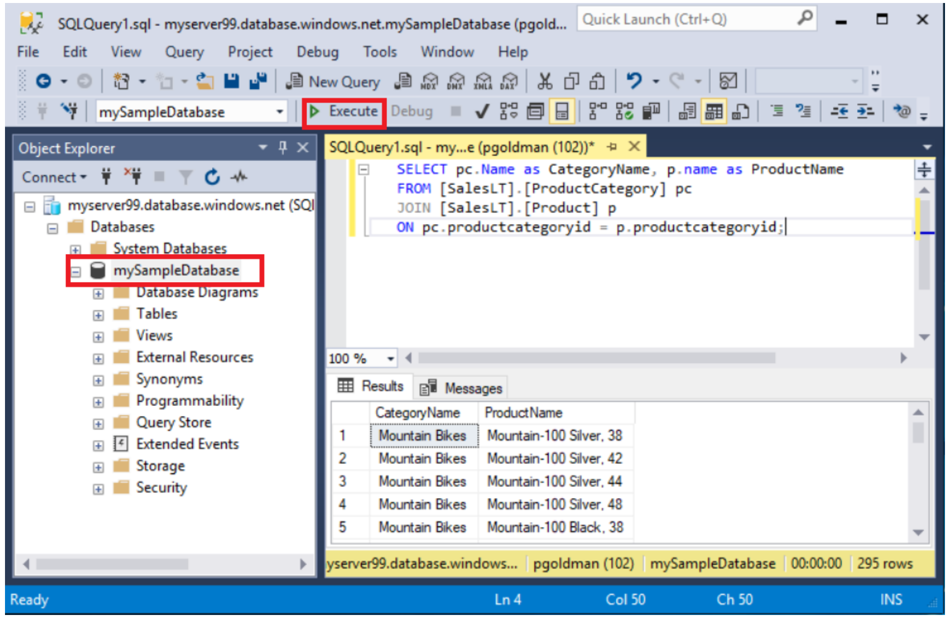
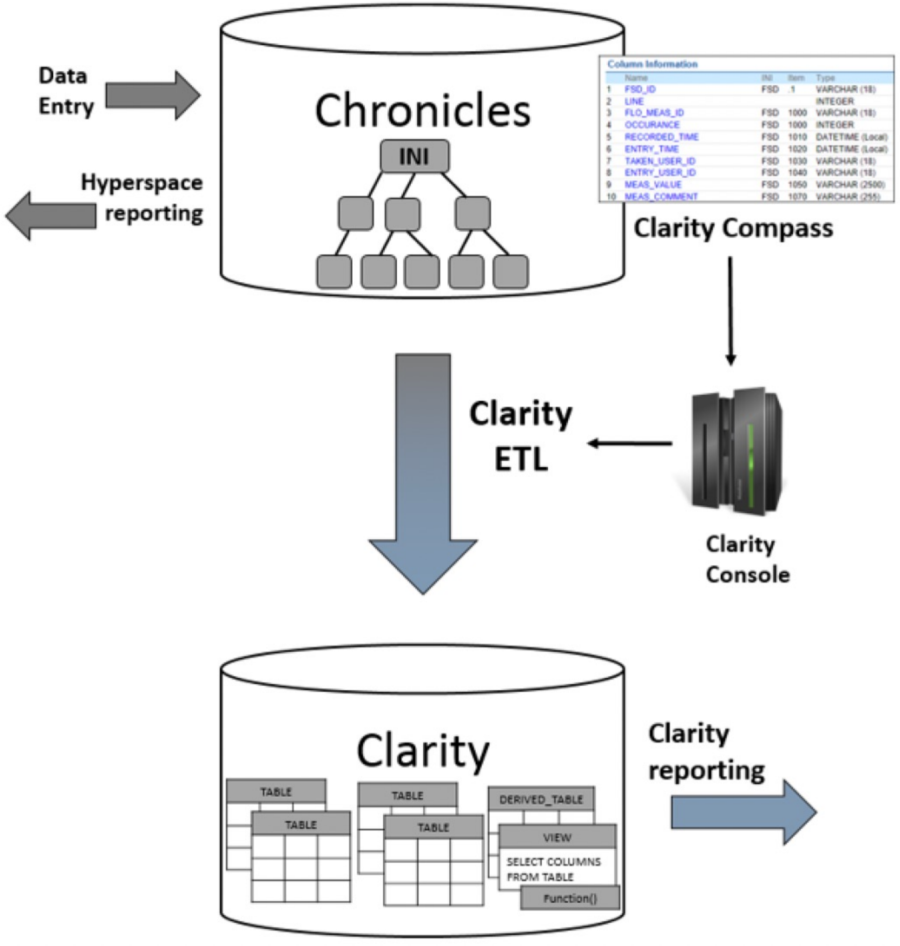
SQL Queries

Don't Share

Data from Chronicles is copied into relational SQL database (Clarity) for reporting/query purposes





Reference: Learn.Microsoft.com

Dashboards

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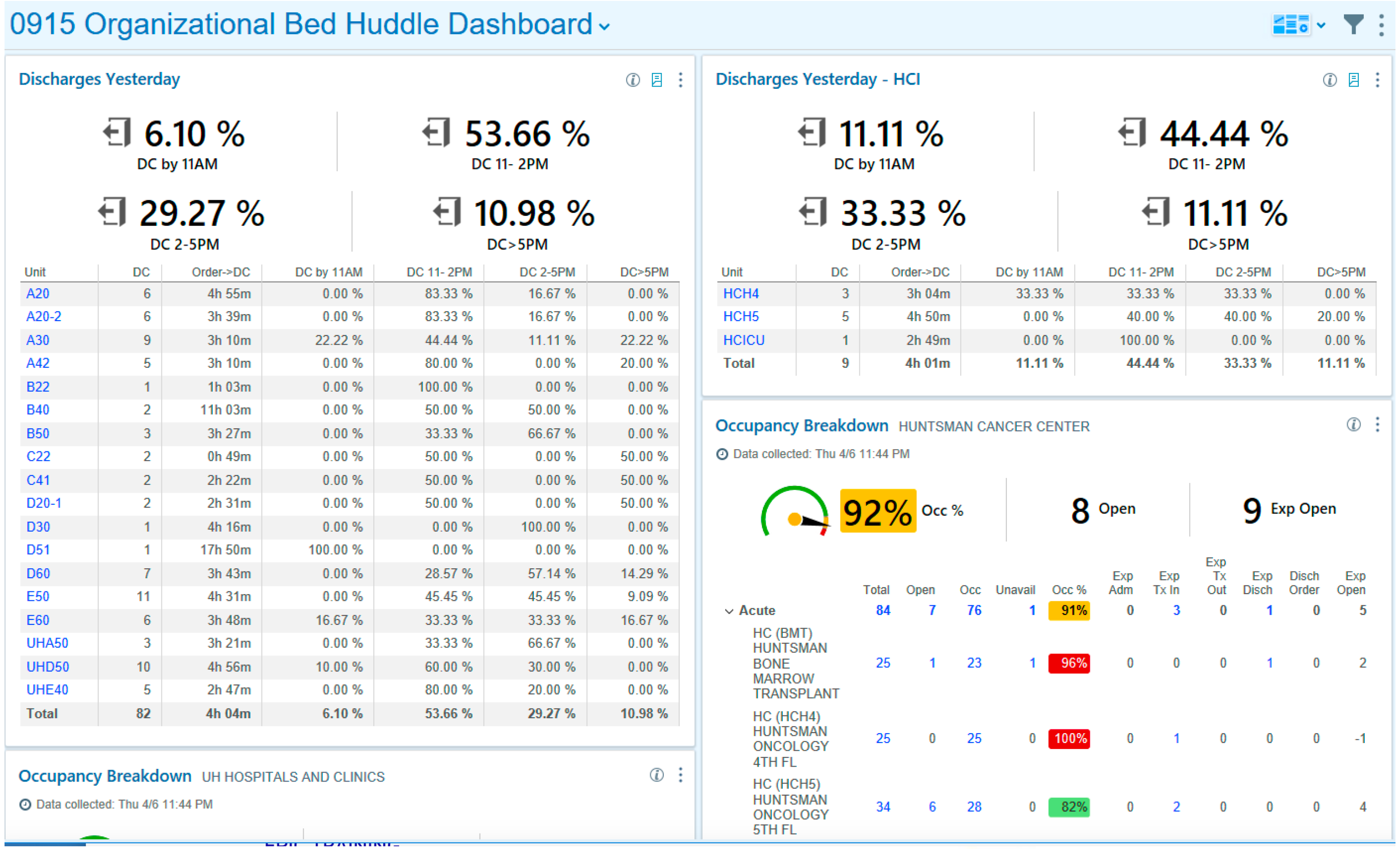
View summary of reports of interest with real-time data

- High-level overview
- Customizable
- Trend data over time



0915 Organizational Bed Huddle Dashboard

Discharges Yesterday

6.10 % DC by 11AM | 53.66 % DC 11- 2PM | 29.27 % DC 2-5PM | 10.98 % DC>5PM

Unit	DC	Order->DC	DC by 11AM	DC 11- 2PM	DC 2-5PM	DC>5PM
A20	6	4h 55m	0.00 %	83.33 %	16.67 %	0.00 %
A20-2	6	3h 39m	0.00 %	83.33 %	16.67 %	0.00 %
A30	9	3h 10m	22.22 %	44.44 %	11.11 %	22.22 %
A42	5	3h 10m	0.00 %	80.00 %	0.00 %	20.00 %
B22	1	1h 03m	0.00 %	100.00 %	0.00 %	0.00 %
B40	2	11h 03m	0.00 %	50.00 %	50.00 %	0.00 %
B50	3	3h 27m	0.00 %	33.33 %	66.67 %	0.00 %
C22	2	0h 49m	0.00 %	50.00 %	0.00 %	50.00 %
C41	2	2h 22m	0.00 %	50.00 %	0.00 %	50.00 %
D20-1	2	2h 31m	0.00 %	50.00 %	0.00 %	50.00 %
D30	1	4h 16m	0.00 %	0.00 %	100.00 %	0.00 %
D51	1	17h 50m	100.00 %	0.00 %	0.00 %	0.00 %
D60	7	3h 43m	0.00 %	28.57 %	57.14 %	14.29 %
E50	11	4h 31m	0.00 %	45.45 %	45.45 %	9.09 %
E60	6	3h 48m	16.67 %	33.33 %	33.33 %	16.67 %
UHA50	3	3h 21m	0.00 %	33.33 %	66.67 %	0.00 %
UHD50	10	4h 56m	10.00 %	60.00 %	30.00 %	0.00 %
UHE40	5	2h 47m	0.00 %	80.00 %	20.00 %	0.00 %
Total	82	4h 04m	6.10 %	53.66 %	29.27 %	10.98 %

Occupancy Breakdown UH HOSPITALS AND CLINICS

Data collected: Thu 4/6 11:44 PM

Discharges Yesterday - HCI

11.11 % DC by 11AM | 44.44 % DC 11- 2PM | 33.33 % DC 2-5PM | 11.11 % DC>5PM

Unit	DC	Order->DC	DC by 11AM	DC 11- 2PM	DC 2-5PM	DC>5PM
HCH4	3	3h 04m	33.33 %	33.33 %	33.33 %	0.00 %
HCH5	5	4h 50m	0.00 %	40.00 %	40.00 %	20.00 %
HCICU	1	2h 49m	0.00 %	100.00 %	0.00 %	0.00 %
Total	9	4h 01m	11.11 %	44.44 %	33.33 %	11.11 %

Occupancy Breakdown HUNTSMAN CANCER CENTER

Data collected: Thu 4/6 11:44 PM

92% Occ % | 8 Open | 9 Exp Open

	Total	Open	Occ	Unavail	Occ %	Exp Adm	Exp Tx In	Exp Tx Out	Exp Disch	Disch Order	Exp Open
Acute	84	7	76	1	91%	0	3	0	1	0	5
HC (BMT) HUNTSMAN BONE MARROW TRANSPLANT	25	1	23	1	96%	0	0	0	1	0	2
HC (HCH4) HUNTSMAN ONCOLOGY 4TH FL	25	0	25	0	100%	0	1	0	0	0	-1
HC (HCH5) HUNTSMAN ONCOLOGY 5TH FL	34	6	28	0	82%	0	2	0	0	0	4

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Reporting Workbench

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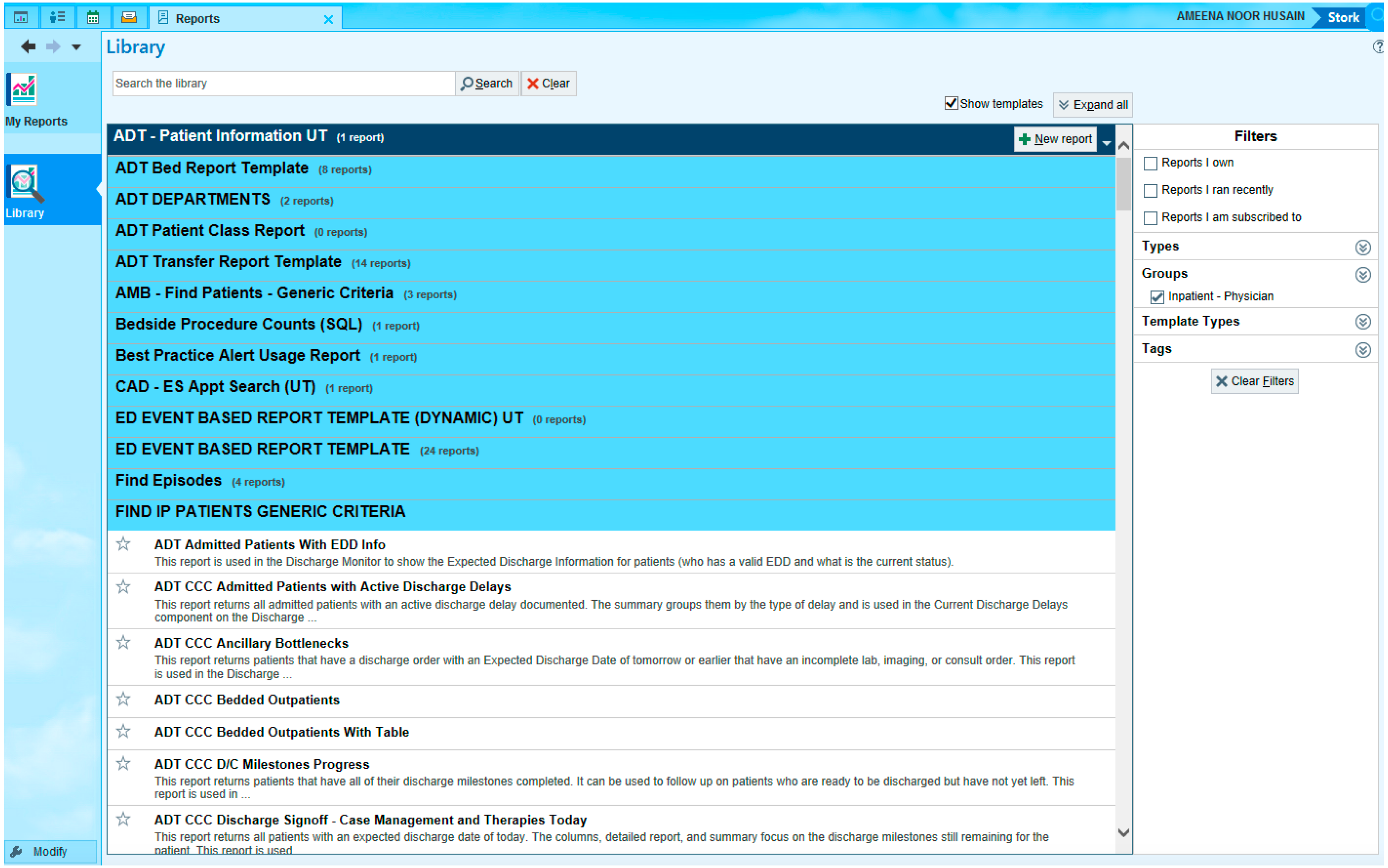
Real-time reports that can be created, changed, and run by the end-user



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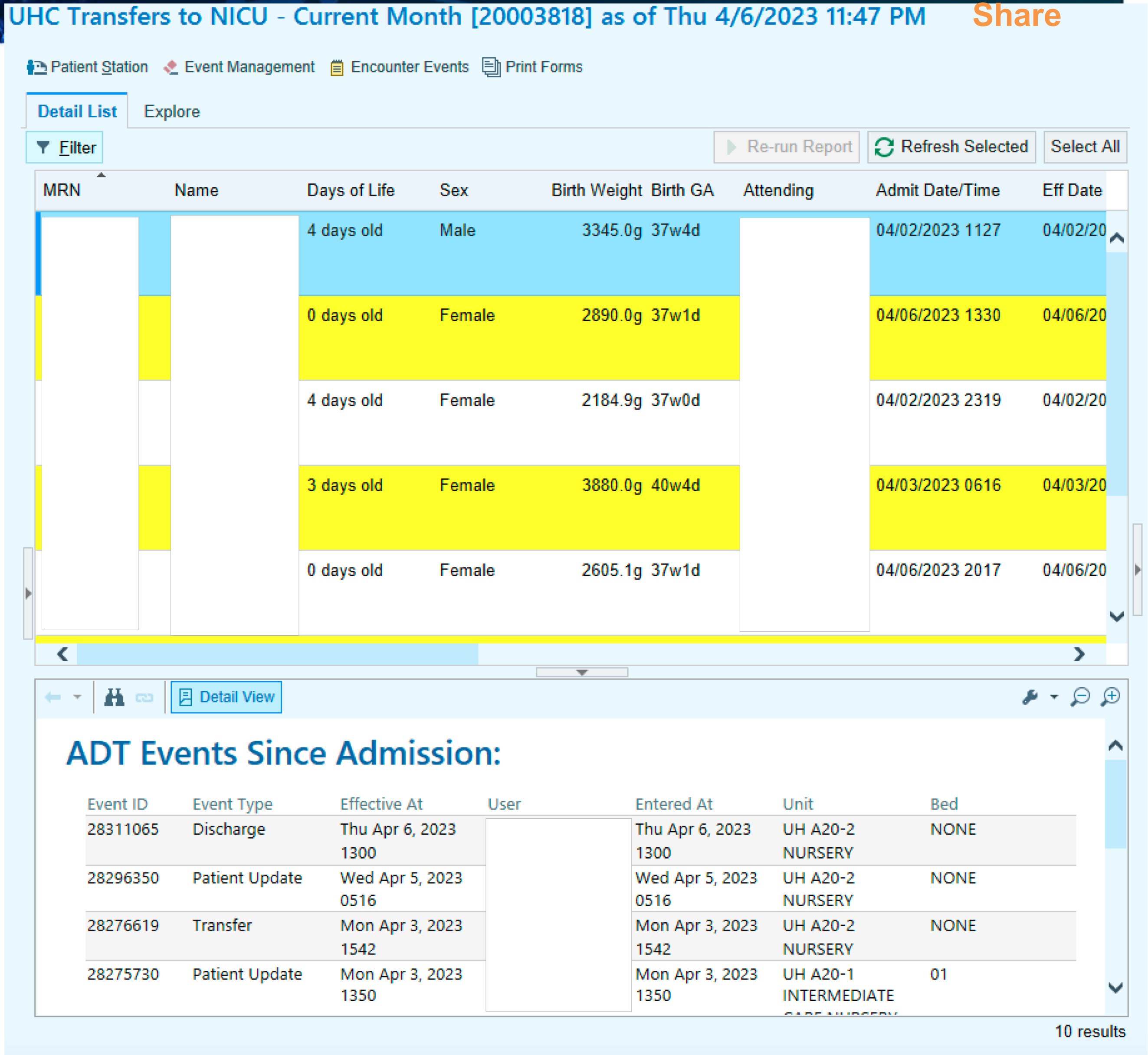
Reporting Workbench

Results in tabular form

Action buttons available depending on type of report

Results can be exported (with appropriate security)



SlicerDicer

Share

Uses:

- Quickly explore large quantities of data
- Show data to patients/families
- Track key performance indicators and follow up with departments or individuals to implement more efficient workflows and reduce costs
- Spot trends over time or based on location
- Find patients for research studies or screening programs
- Design dashboards with embedded self-service options

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SlicerDicer

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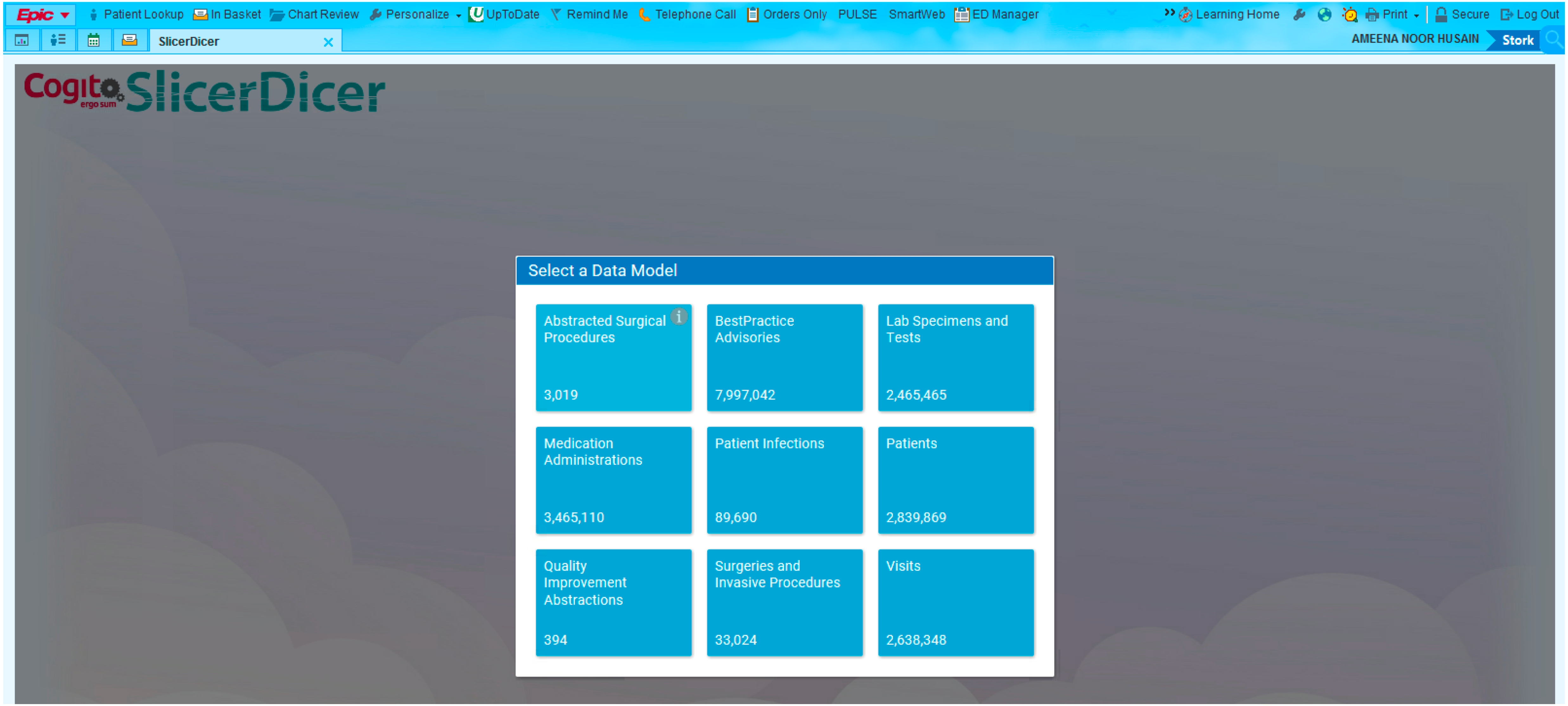

SlicerDicer

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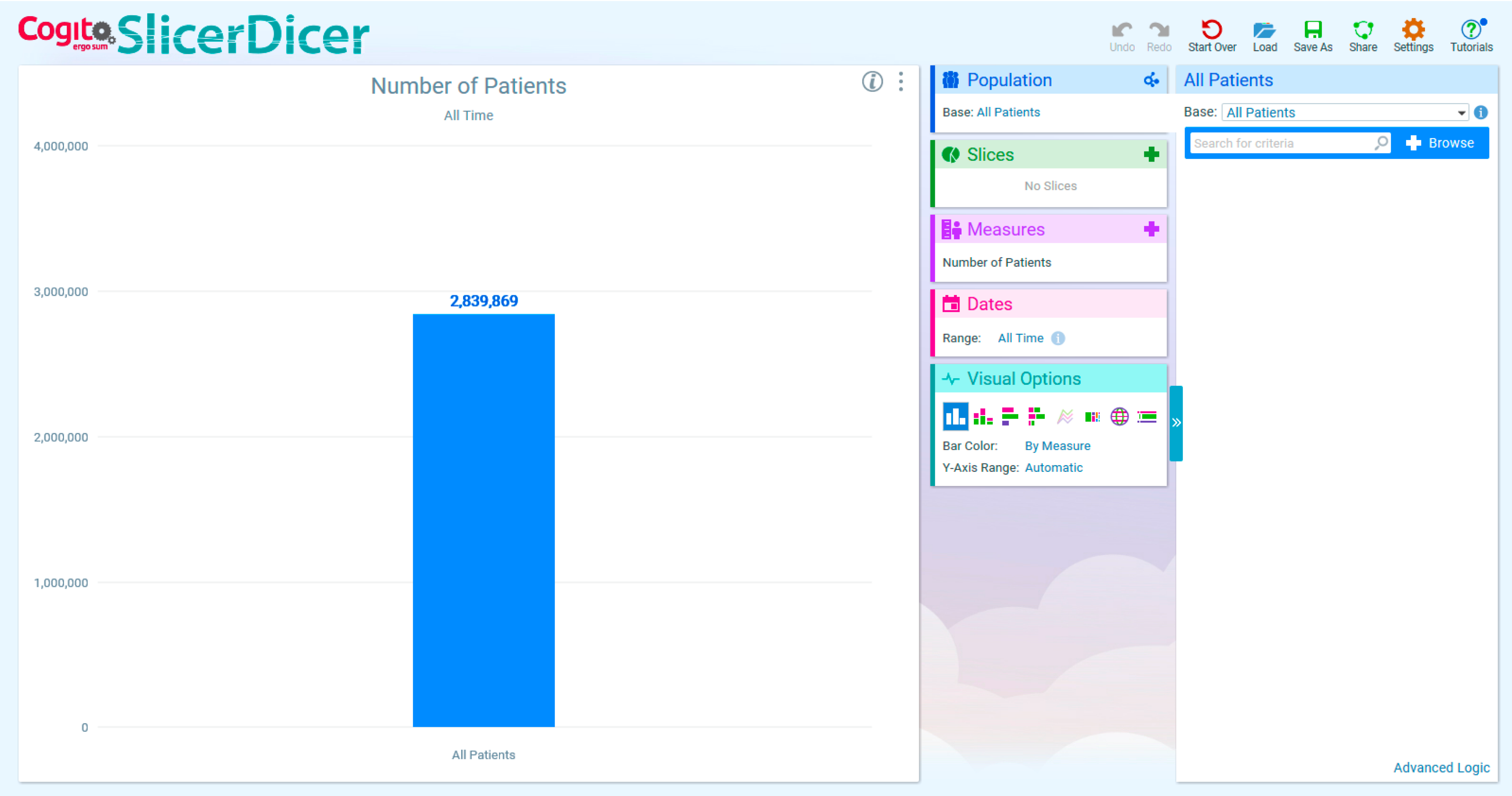

SlicerDicer

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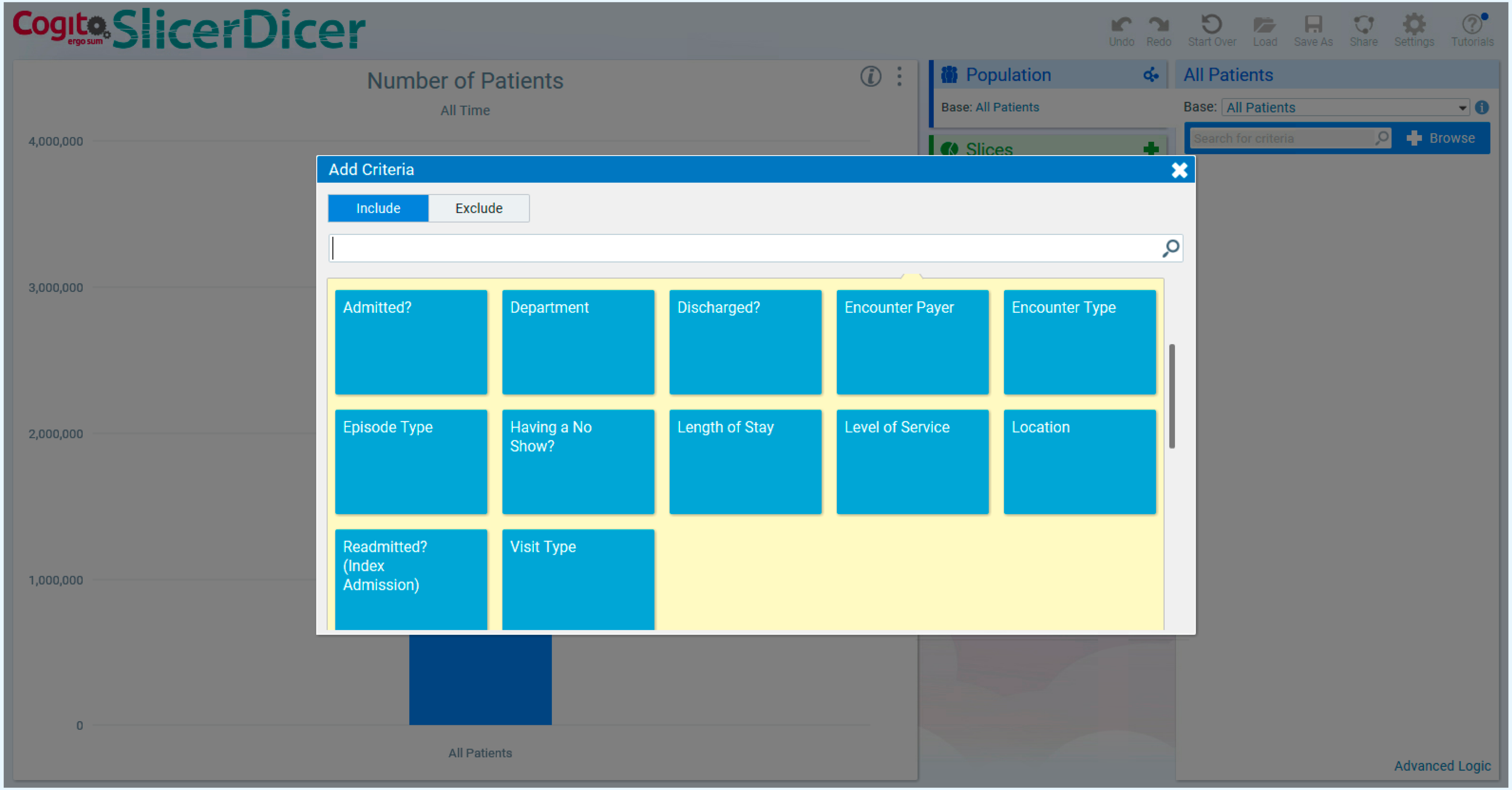
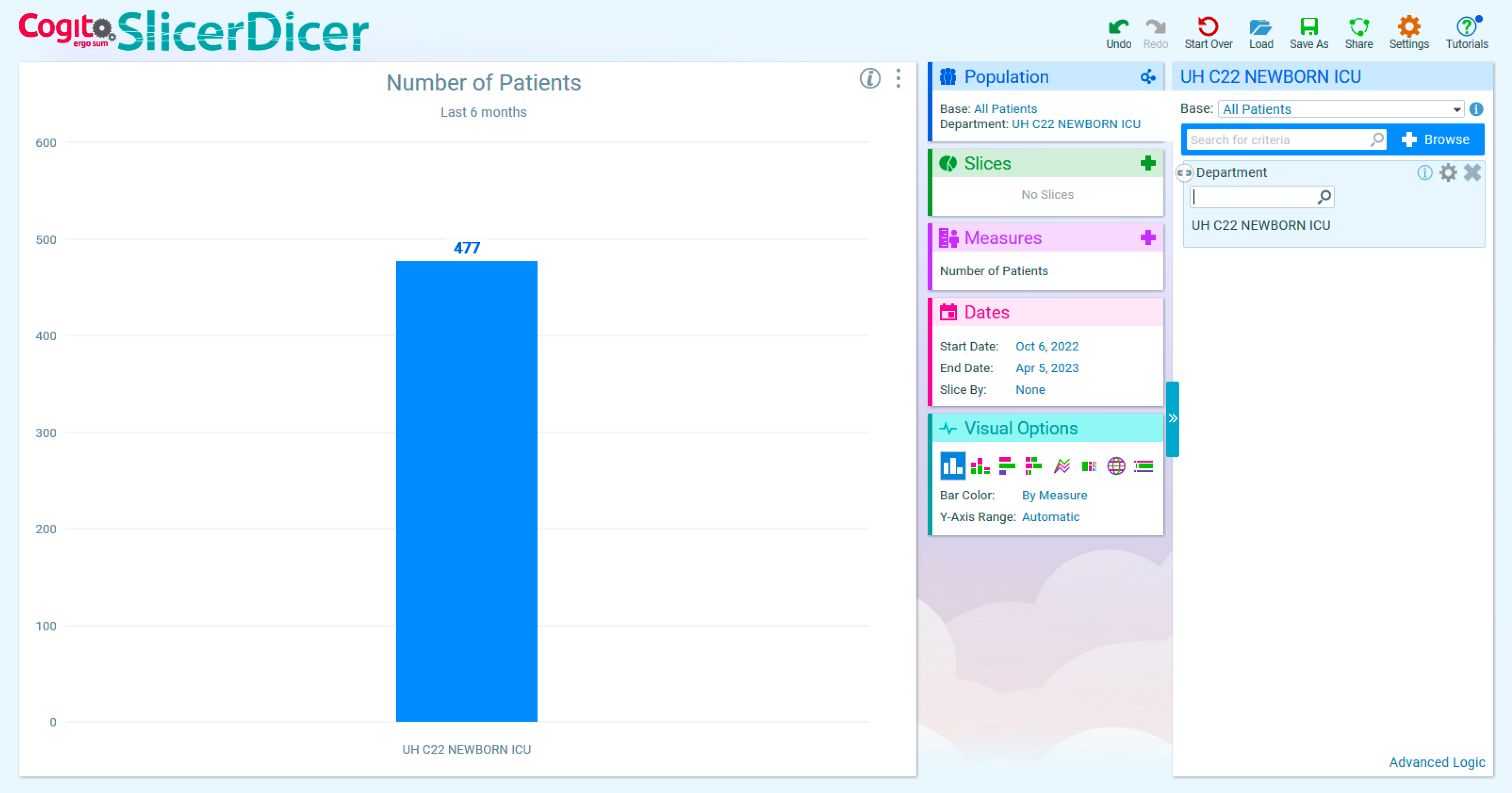


SlicerDicer

Share



SlicerDicer Features

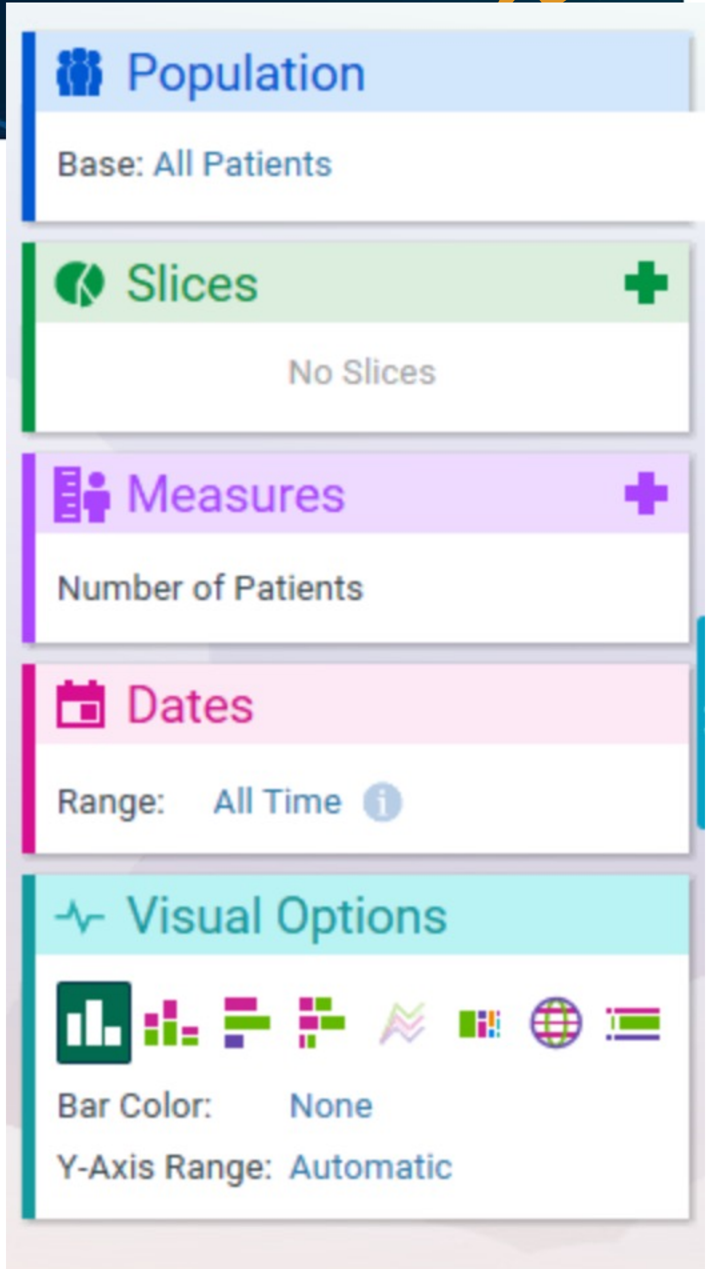
Population: defines the data that will be used by the data model. Criteria can be added to further narrow the data set.

Slices: divide your population into categories so you can compare differences between those groups.

Measures: control the calculation that appears on the graph. For example, you can see total counts, averages, or percentages for different aspects of the population.

Dates: when data is tracked over time, results on the graph are limited to a specific date range and can be sliced by date intervals to see trends.

Visual options: control how the graph looks. Change elements like the graph type, measure or colors.



SlicerDicer

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SlicerDicer Limitations

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- Good tool for finding patients of interest, not for telling you about them
- Draws from data at least one day old → cannot be used for real-time reporting
- Can only search certain discrete data
- Data model determines results
  - Ex: search for patients who had an ED visit
    - In Patients data model → returns patients who had at least one ED visit; cannot tell if single patient went to ED multiple times
    - In ED Encounters data model → one result for each ED visit even if some are for the same patient ; cannot see distinct number of patients who went to ED

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Challenges of EHR Tools

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- Data mapping and validation
  - Structured vs unstructured data
  - Data availability and accuracy
- Site variation - location of data, naming conventions, definitions
- Lack of standardization and interoperability
- Lack of current NICU specific fields available in tools such as SlicerDicer
  - Encourage your IT team/leadership to expand available fields for the data of most value to you

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Want to learn more?

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- Play, explore, practice
  - Access requests: exporting data, record viewer, editing reports
  - Partner with IT team for expansion of NICU specific fields

- Epic Training (https://training.epic.com)
  - Discuss with IT leadership
  - Consider becoming a physician builder

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Overview of Machine Learning Tools

Kristyn Beam
Beth Israel Deaconess

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Overview of machine learning tools

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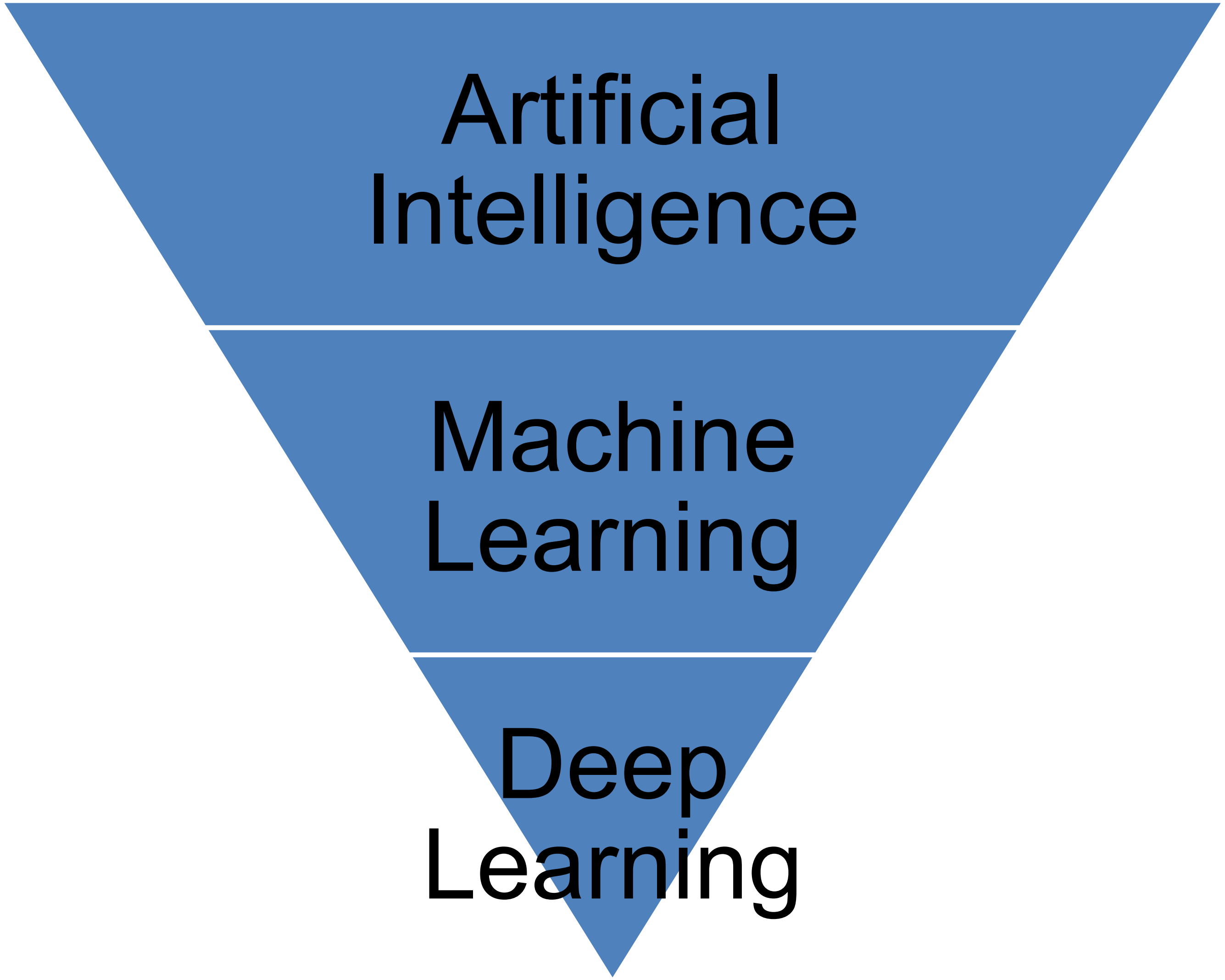

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Last Decade of AI

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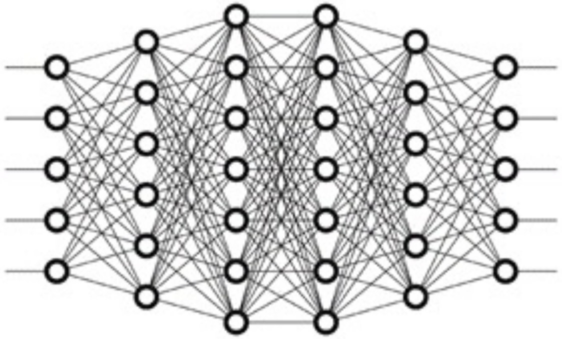
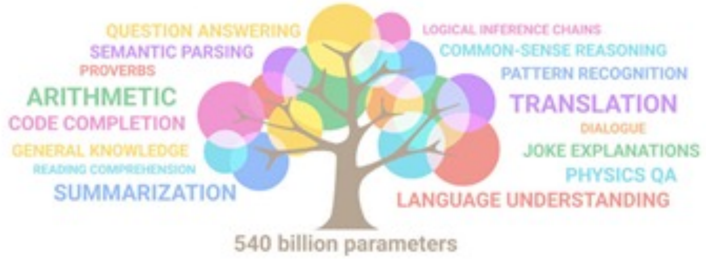
- AI has made leaps and bounds over the last 10 years

Supervised Learning (2012 - 2017)
- Large models trained to predict massive amounts of **labeled data**



Self-supervised Learning (2017 – present)
- Generalist models capable of doing many tasks that **do not require labels**



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Supervised Learning

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Ophthalmology

This Issue Views 60,378 | Citations 2 | Altmetric 633

Original Investigation | Innovations in Health Care Delivery

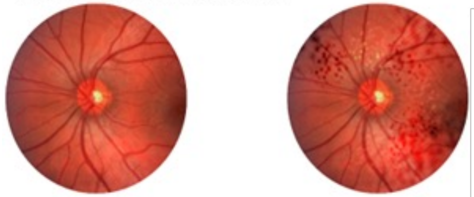
December 13, 2016

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Varun Gulshan, PhD[1]; Lily Peng, MD, PhD[1]; Marc Coram, PhD[1]; et al

> Author Affiliations

JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216



Dermatology

Published: 25 January 2017

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva, Brett Kuprel, Roberto A. Novoa, Justin Ko, Susan M. Swetter, Helen M. Blau & Sebastian Thrun

Nature 542, 115–118(2017) | Cite this article

55k Accesses | 2394 Citations | 2871 Altmetric | Metrics

A Corrigendum to this article was published on 29 June 2017

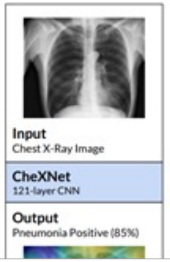
Radiology

CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pranav Rajpurkar *1 Jeremy Irvin *1 Kaylie Zhu 1 Brandon Yang 1 Hershel Mehta 1 Tony Duan 1 Daisy Ding 1 Aarti Bagul 1 Robyn L. Ball 2 Curtis Langlotz 3 Katie Shpanskaya 3 Matthew P. Lungren 3 Andrew Y. Ng 1

Abstract

We develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. Four practicing academic radiologists annotate a test set, on which we compare the performance of CheXNet to that of radiologists. We find that CheXNet exceeds average radiologist performance on the F1 metric. We extend CheXNet to detect all 14 diseases in ChestX-ray14 and achieve state of the art results on all 14 diseases.



These techniques have resulted in physician level performance in many areas of diagnostic medical imaging

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Self-Supervised Learning

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If we don't have enough **labels**, self-supervision is way to train a model in a very generic way

<u>Trick:</u> Train the model to play a "game" on the data that you have. This often involves hiding some part of the data and training the model to "guess" what the hidden part contains

If the model learns to play the game well, it will be able to do other tasks that "look like" the game it's learned to play.

Large Language Models

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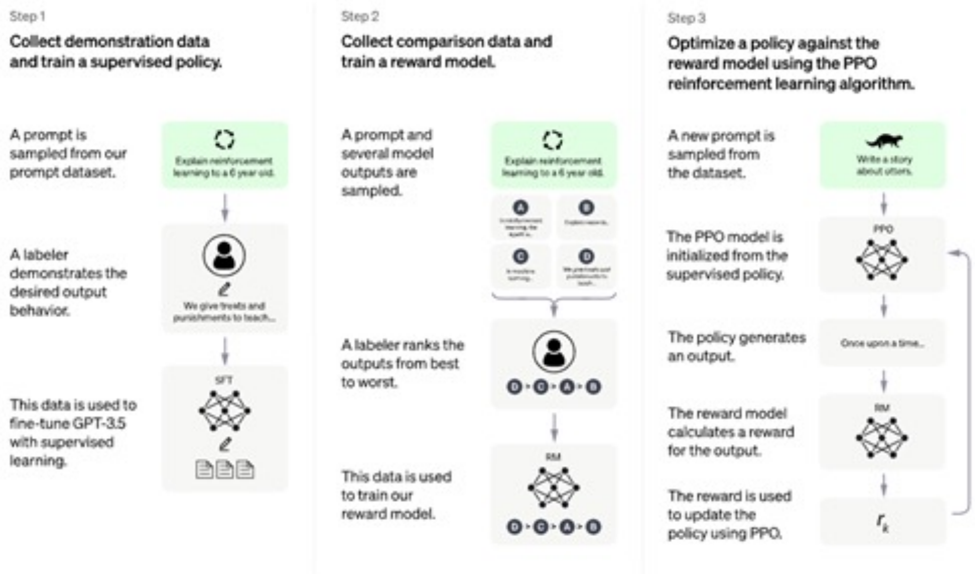
Chat-GPT is one of the most well-known self-supervised models

- Allows us to ask questions that are not possible with supervised learning models

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.



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Why AI for the NICU?

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DATA!

Physiologic parameters

Delivery room information

Vasoactives

Nutrition

Ventilator data

Antibiotics

Environment: single vs bay

Pain control

Parental involvement

Neurologic monitoring

Exam

Temperature regulation

Laboratory data

https://www.reporternewsatom/story/news/2018/07/05/hendricks-nicu-earns-special-designation-level-iii-neonatal-facility/755590002/

NICU Supervised Learning

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- Sepsis risk prediction
- BPD Calculators
- ROP Screening and Diagnosis
- Many others

RESEARCH ARTICLE

PREMATURE INFANTS

Integration of Early Physiological Responses Predicts Later Illness Severity in Preterm Infants

Suchi Saria,[1] Anand K. Rajani,[2] Jeffrey Gould,[2] Daphne Koller,[1]* Anna A. Penn[2]*

(Published 8 September 2010; Volume 2 Issue 48 48ra65)

Physiological data are routinely recorded in intensive care, but their use for rapid assessment of illness severity or long-term morbidity prediction has been limited. We developed a physiological assessment score for preterm newborns, akin to an electronic Apgar score, based on standard signals recorded noninvasively on admission to a neonatal intensive care unit. We were able to accurately and reliably estimate the probability of an individual preterm infant's risk of severe morbidity on the basis of noninvasive measurements. This prediction algorithm was developed with electronically captured physiological time series data from the first 3 hours of life in preterm infants (≤34 weeks gestation, birth weight ≤2000 g). Extraction and integration of the data with state-of-the-art machine learning methods produced a probability score for illness severity, the PhysiScore. PhysiScore was validated on 138 infants with the leave-one-out method to prospectively identify infants at risk of short- and long-term morbidity. PhysiScore provided higher accuracy prediction of overall morbidity (86% sensitive at 96% specificity) than other neonatal scoring systems, including the standard Apgar score. PhysiScore was particularly accurate at identifying infants with high morbidity related to specific complications (infection: 90% at 100%; cardiopulmonary: 96% at 100%). Physiological parameters, particularly short-term variability in respiratory and heart rates, contributed more to morbidity prediction than invasive laboratory studies. Our flexible methodology of individual risk prediction based on automated, rapid, noninvasive measurements can be easily applied to a range of prediction tasks to improve patient care and resource allocation.

CURRENT OPINION

Predictive monitoring for early detection of sepsis in neonatal ICU patients

Karen D. Fairchild

Purpose of review
Predictive monitoring is an exciting new field involving analysis of physiologic data to detect abnormal patterns associated with critical illness. The first example of predictive monitoring being taken from inception (proof of concept) to reality (demonstration of improved outcomes) is the use of heart rate characteristics (HRC) monitoring to detect sepsis in infants in the neonatal ICU. The commercially available 'HeRO' monitor analyzes electrocardiogram data from existing bedside monitors for decreased HR variability and transient decelerations associated with sepsis, and converts these changes into a score (the HRC index or HeRO score). This score is the fold increase in probability that a patient will have a clinical deterioration from sepsis within 24 h. This review focuses on HRC monitoring and discusses future directions in predictive monitoring of ICU patients.

Recent findings
In a randomized trial of 3003 very low birthweight infants, display of the HeRO score reduced mortality more than 20%. Ongoing research aims to combine respiratory and HR analysis to optimize care of ICU patients.

Summary
Predictive monitoring has recently been shown to save lives. Harnessing and analyzing the vast amounts of physiologic data constantly displayed in ICU patients will lead to improved algorithms for early detection, prognosis, and therapy of critical illnesses.

Keywords
heart rate variability, ICU, neonate, predictive monitoring, prematurity, sepsis

Research

JAMA Ophthalmology | Original Investigation

Automated Diagnosis of Plus Disease in Retinopathy of Prematurity Using Deep Convolutional Neural Networks

James M. Brown, PhD; J. Peter Campbell, MD, MPH; Andrew Beers, BA; Ken Chang, MSE; Susan Ostmo, MS; R. V. Paul Chan, MD; Jennifer Dy, PhD; Deniz Erdogmus, PhD; Stratis Ioannidis, PhD; Jayashree Kalpathy-Cramer, PhD; Michael F. Chiang, MD; for the Imaging and Informatics in Retinopathy of Prematurity (i-ROP) Research Consortium

Supplemental content

IMPORTANCE Retinopathy of prematurity (ROP) is a leading cause of childhood blindness worldwide. The decision to treat is primarily based on the presence of plus disease, defined as dilation and tortuosity of retinal vessels. However, clinical diagnosis of plus disease is highly subjective and variable.

OBJECTIVE To implement and validate an algorithm based on deep learning to automatically diagnose plus disease from retinal photographs.

BPD Prediction

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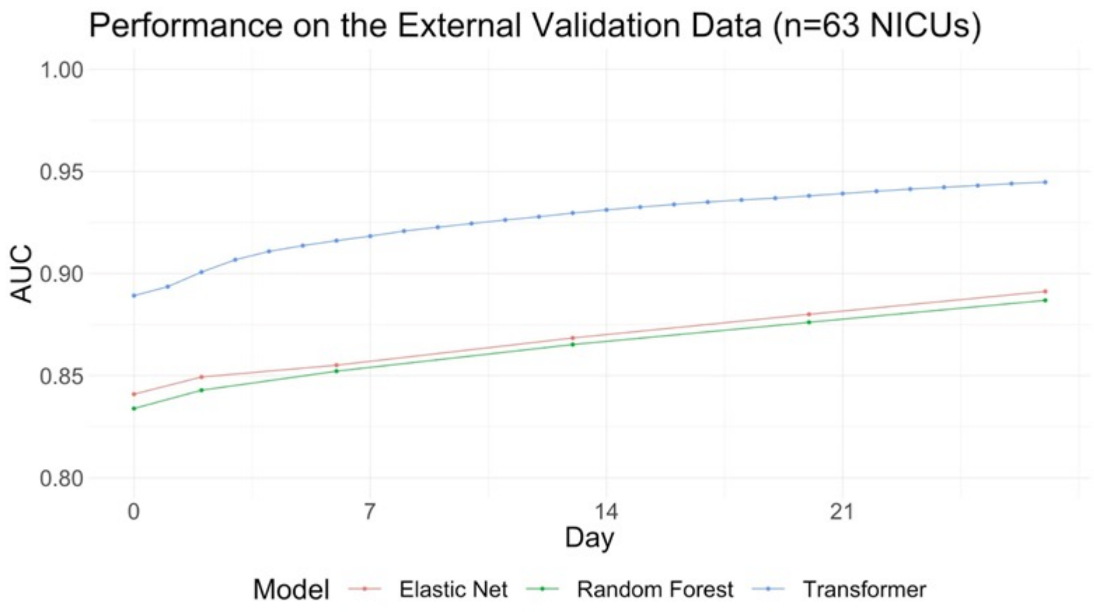
- Our model achieves an AUC of 0.87 on the first day of life and reaches ~0.95 by day 28

- Previous models in the literature range from 0.6-0.7 on the first day of life and 0.7-0.85 by day 28



Beam et al.. Predicting Daily Bronchopulmonary Dysplasia Risk with Artificial Intelligence and Deep Learning. PAS 2022

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Chat-GPT in Neonatology

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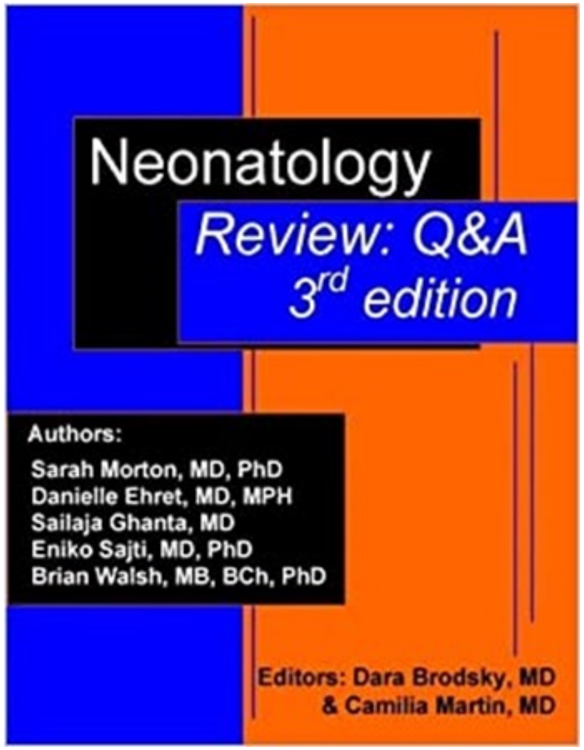
- What do large language models know about neonatology?
- We wanted to find out!
- We entered each question manually, asked for ChatGPT's best answer and a justification



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Beam et al.. Predicting Daily Bronchopulmonary Dysplasia Risk with Artificial Intelligence and Deep Learning. PAS 2022

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Chat-GPT in Neonatology

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Results: 47% correct

Large variability in accuracy
- 40% to 78%

The explanations were graded by Dr. Brodsky and Dr. Martin

Table 1: Accuracy of ChatGPT on Neonatal Board Practice Questions

Subject	Total # of Questions	Eligible Questions After Exclusion	% Correct, (Average)	% Correct, First Rater	% Correct, Second Rater	Inter-rater Agreement	Average # Responses per Question
MFM	139	136	47.06	48.53	45.59	88.24	4.87
Respiratory	87	81	39.27	39.02	39.51	90.12	4.88
Cardiology	57	51	41.13	45.00	37.25	86.27	4.76
Neurology	97	93	52.15	47.31	56.99	84.95	4.80
Genetics	85	81	45.12	45.12	45.12	85.37	4.90
ID	110	104	43.47	40.78	46.15	82.69	5.00
Fluids	107	102	45.10	47.06	43.14	80.39	4.79
GI	45	40	40.00	42.50	37.50	92.50	4.98
Hematology	64	61	40.67	38.71	42.62	86.89	4.87
Endocrinology	75	75	43.05	42.10	44.00	88.00	4.84
Metabolism	33	30	41.36	39.39	43.33	86.67	4.90
Pharmacology	71	68	51.47	52.94	50.00	85.29	4.82
Ethics	14	14	78.50	78.50	78.50	1.00	4.71
Overall	984	936	46.80	46.69	46.90	86.22	4.86

Beam, K. et. al Assessment of ChatGPT Pediatric Subspeciality Knowledge on Neonatal Board Examination Questions (under review)

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Introduction to Data Analytics

Brynne Sullivan
University of Virginia

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NICU Data Sources

Share

- Baseline, static data
  - Patient demographics
  - Maternal health and delivery history

- Clinician-initiated data
  - Medications
  - Imaging
  - Procedures, interventions, support devices
  - Laboratory results
  - Notes
  - Diagnoses

NICU Data Sources

Share

- Patient-generated data
  - Continuous bedside monitoring
    - ECG heart rate
    - Pulse oximetry pulse rate and SpO2
    - Chest impedance respiratory rate
    - Arterial blood pressure (sometimes)
  - Intermittent but frequent
    - Cuff blood pressure
    - Temperature

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Physiologic data- new information

Share

- HR, SpO2, RR: routinely measured continuously in the NICU, making the information they contain entirely patient-generated
- Autonomic nervous system response to illness alters control of heart rate and breathing
- Changes in the continuous cardiorespiratory monitoring data contain the earliest signs of deterioration
- EHR data tell you what you already know- reflects orders and decisions in response to physiologic changes

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Predictive analytics: examples

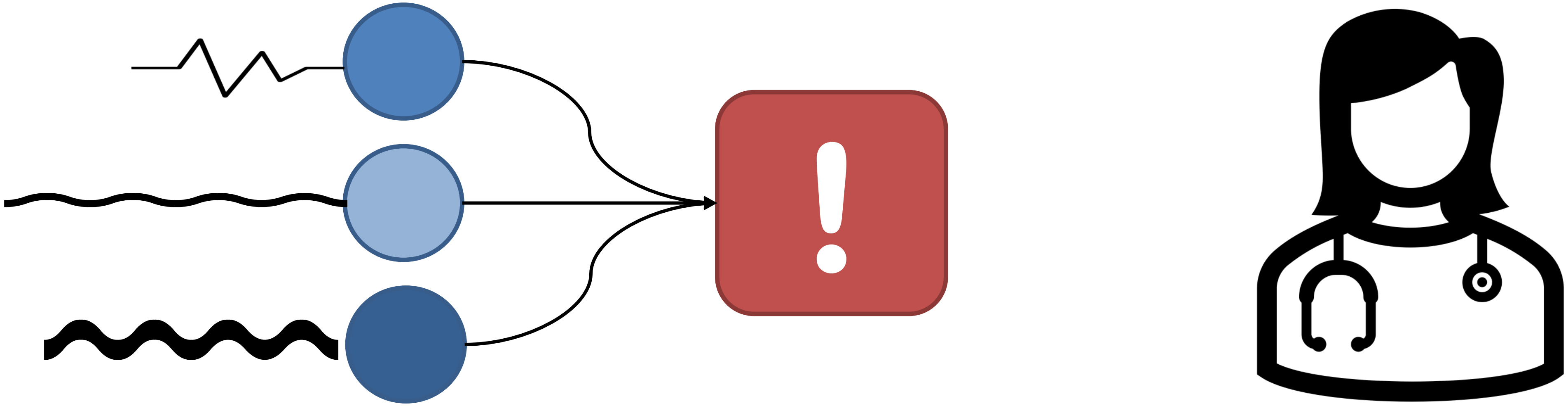
Share

- When we can determine that signatures of illness are present, we can contemplate using statistical models as bedside predictive tools.

  - Heart rate characteristics monitoring
  - Cardiorespiratory analytics
  - Motion detection

Predictive Monitoring

Don't Share



Data

Predictive modeling

Predicted risk

Clinical decision

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Early Warning: before overt signs

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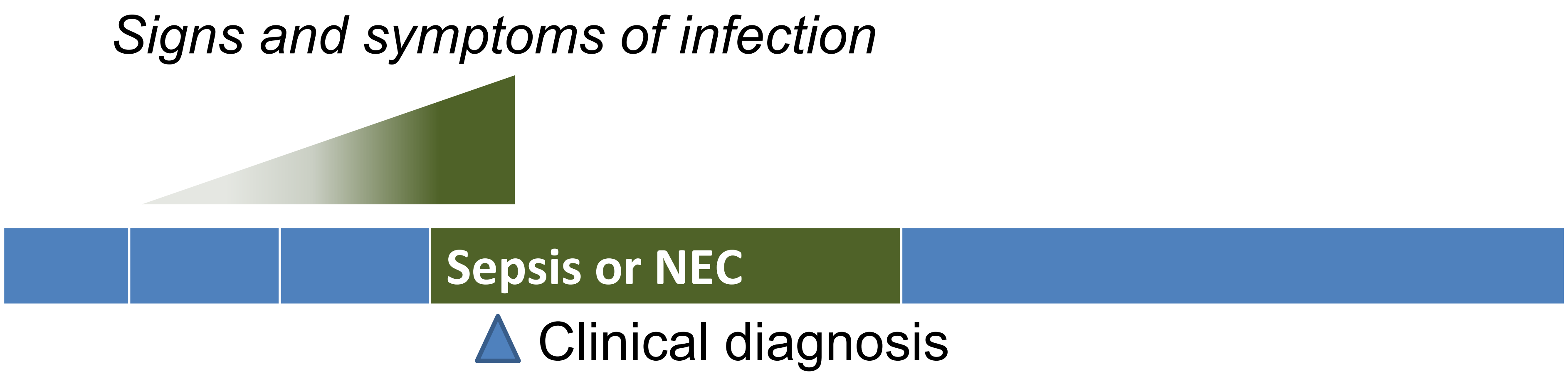

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Early Warning: before overt signs

Don’t Share

Signs and symptoms of infection

Early Warning

Predictive Monitoring

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Heart Rate Characteristics Index

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HRC Index, 5 days

Heart Rate, 30 minutes

(HeRO Score)

Current predicted risk of sepsis

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HRC Index (HeRO Score)

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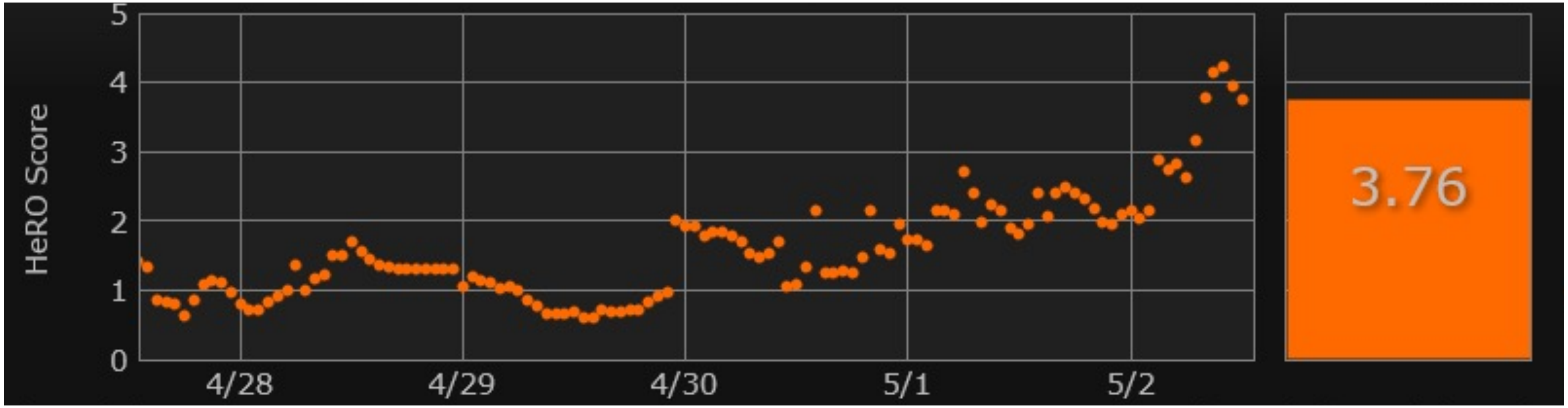


- Display of HRC index reduced all-cause mortality 20% in multicenter RCT of 3,000 VLBW infants (Moorman, et al. *J Pediatrics* 2011)
- 40% reduction in death within 30 days of septicemia (Fairchild, et al. *Peds Research* 2013)

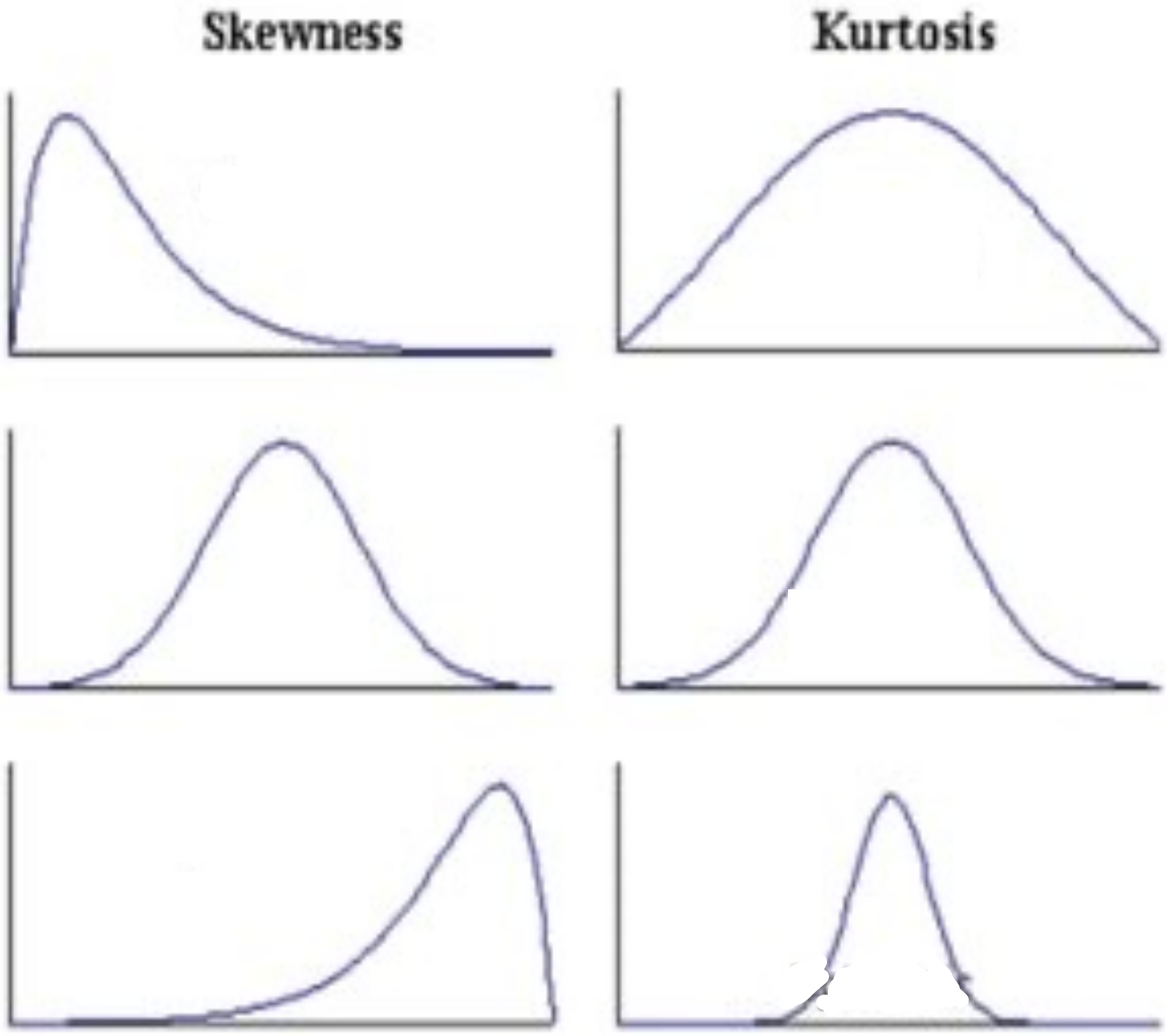
Cardiorespiratory model features

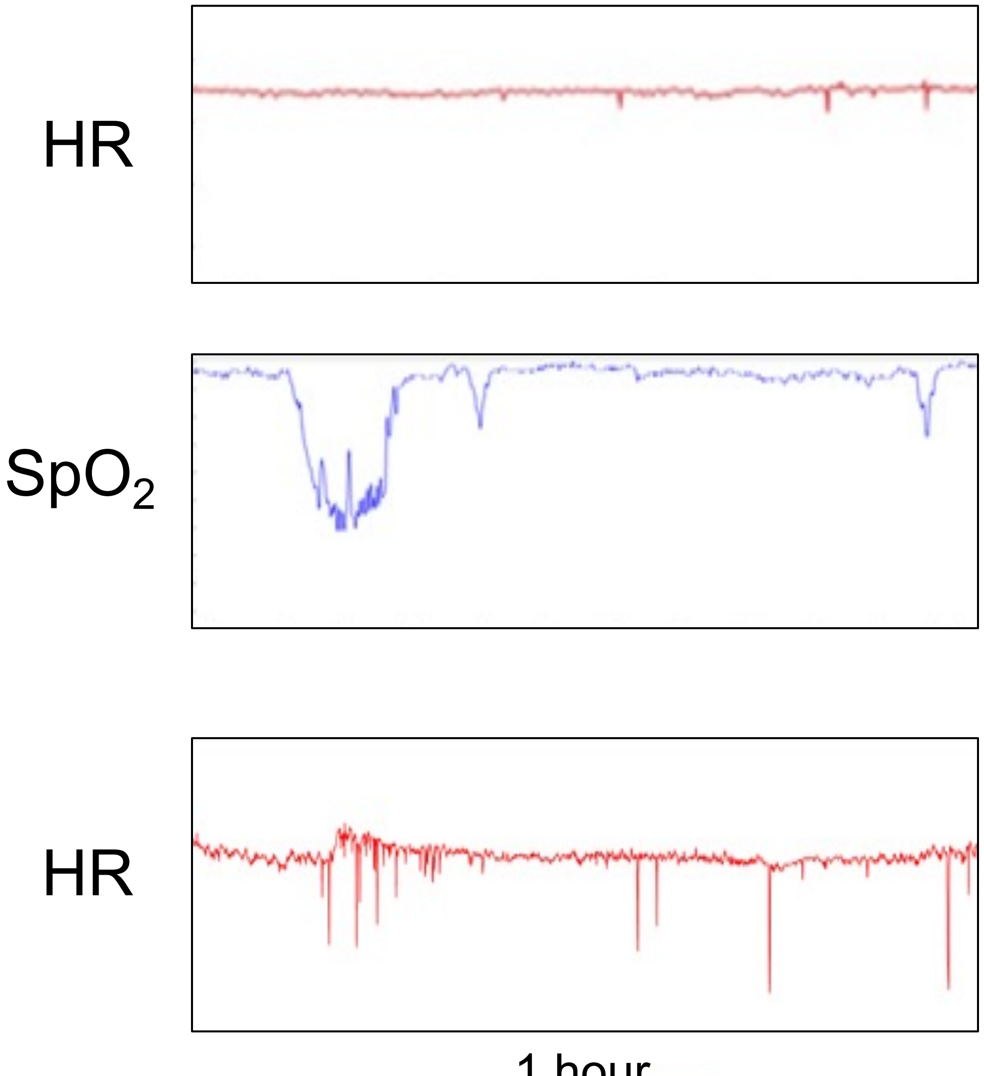
Don't Share

10 features calculated every 10 minutes from the raw data

HR	SpO_2
Mean	Mean
Standard Deviation	Standard Deviation
Skewness	Skewness
Kurtosis	Kurtosis
Minimum and Maximum Cross-Correlation	

Cardiorespiratory predictive monitoring





POWS: normal & sepsis examples

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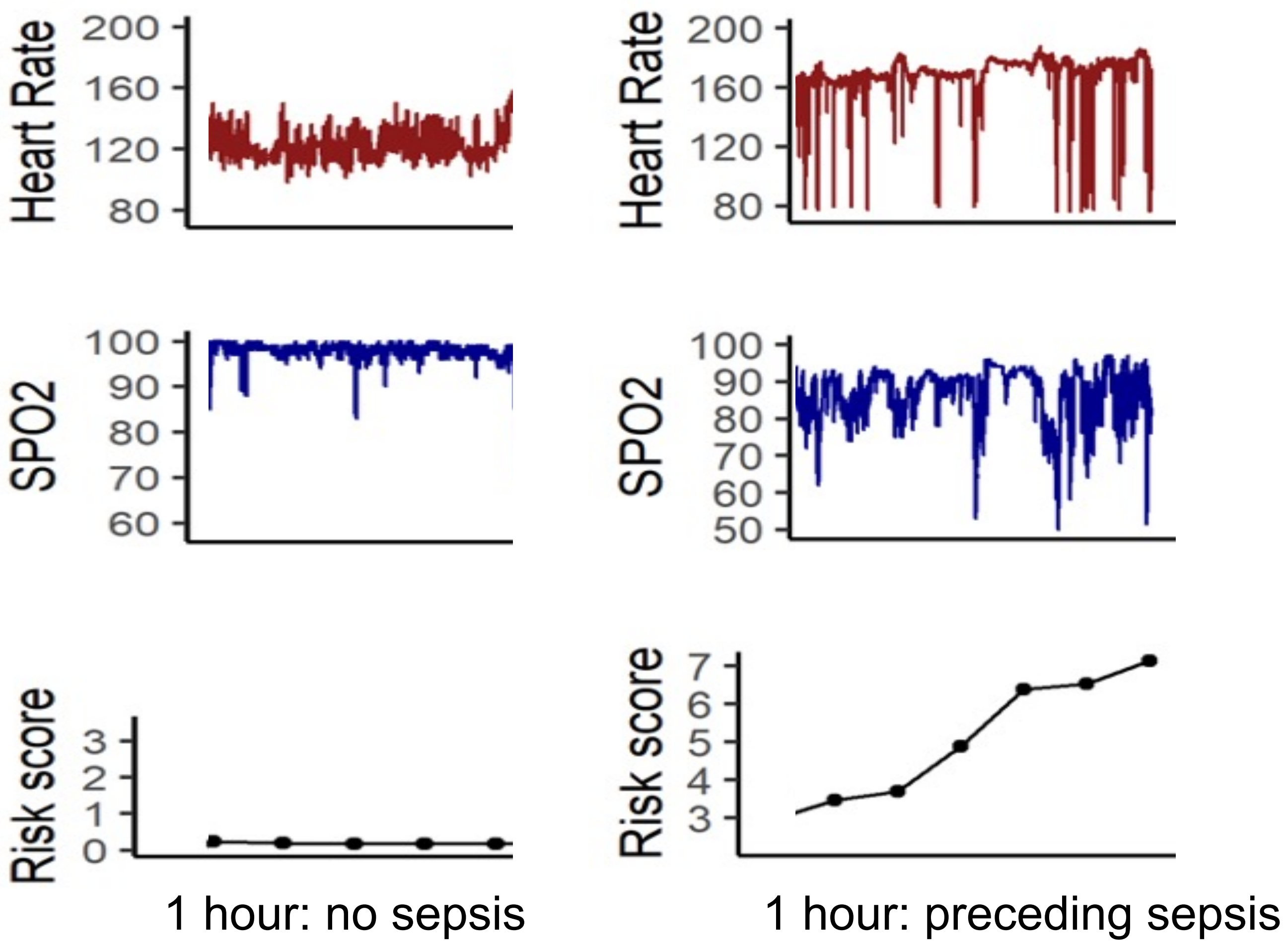

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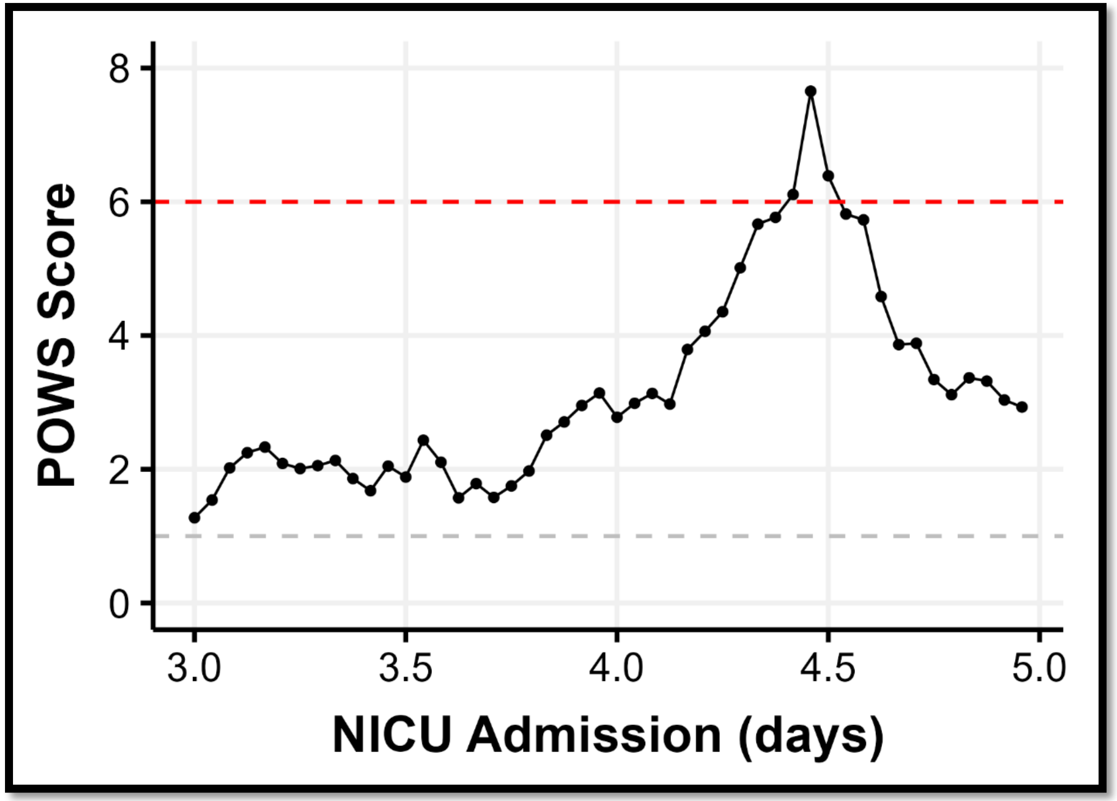
Predictive analytics: alerts

Share



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Soup to Nuts: steps of development

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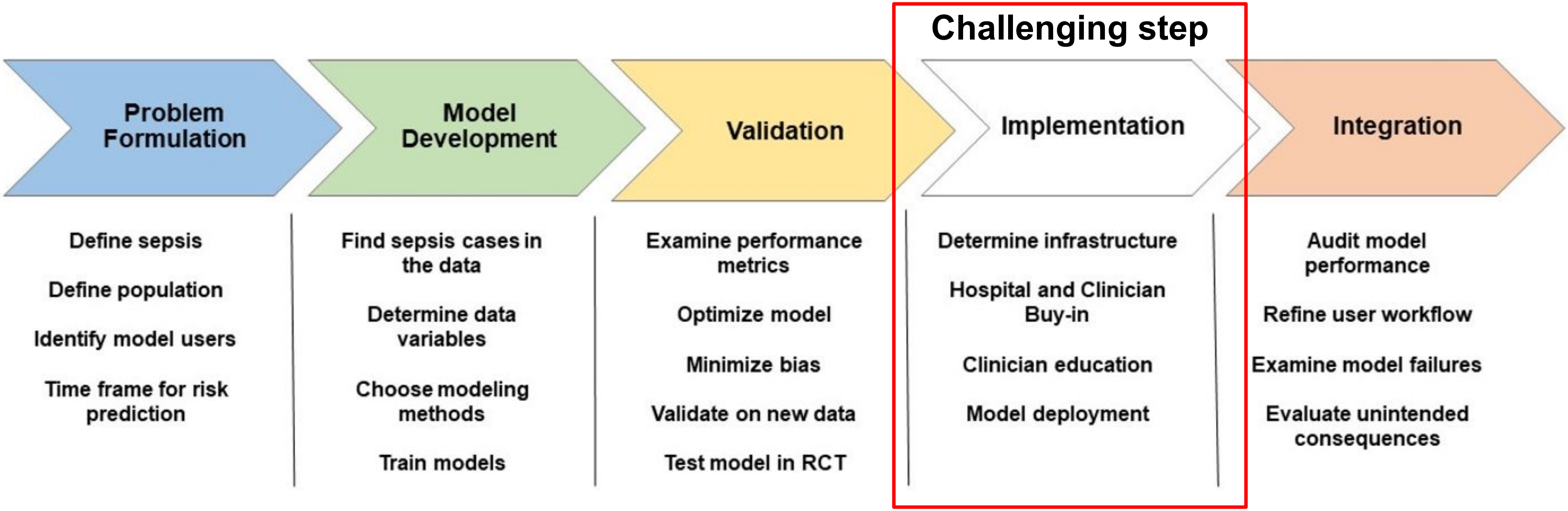

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Implementation

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How do we display and use the information?

Users

Alarms

Equipment

Education

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Artificial + Human intelligence

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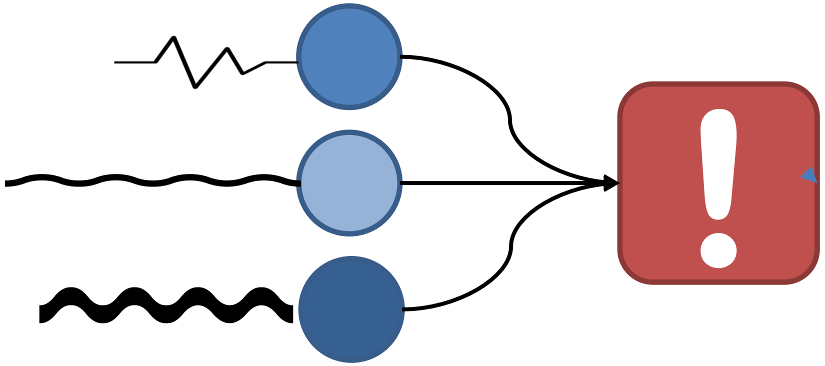
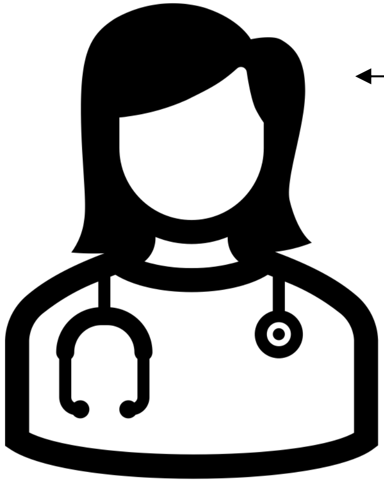
Clinical assessment, risk factors

Predictive monitoring using physiologic data





Laboratory data

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The future: collaboration

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Live Demonstrations in Octave and R Studio

Zachary Vesoulis
Washington University

Share

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Sample Case Walkthrough

Brynne Sullivan
University of Virginia

Zachary Vesoulis
Washington University

Share

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Case 1: Sepsis

Share

- 2-week old, 27-week male infant on CPAP
- Nurse mentions and increase in apnea events and bradycardia alarms on morning rounds
- Physical exam and labs are reassuring

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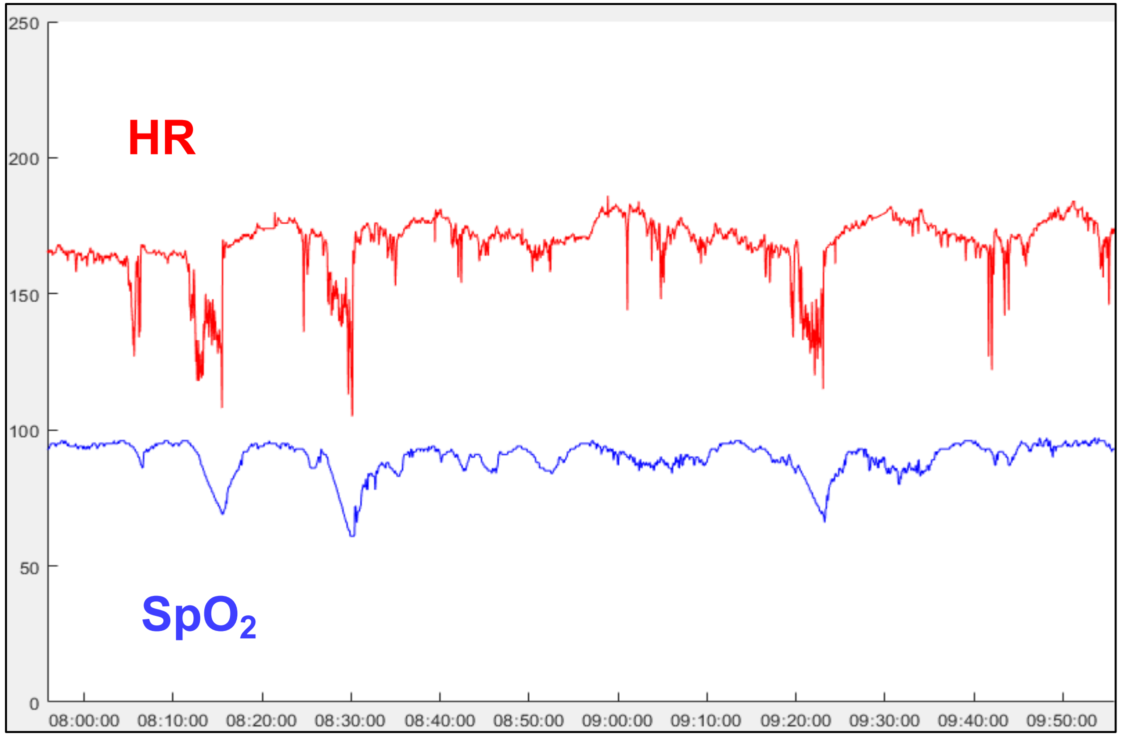
Case 1: Sepsis

Don't Share

2-Hour trend of HR and SpO2



Normal bedside vitals on rounds

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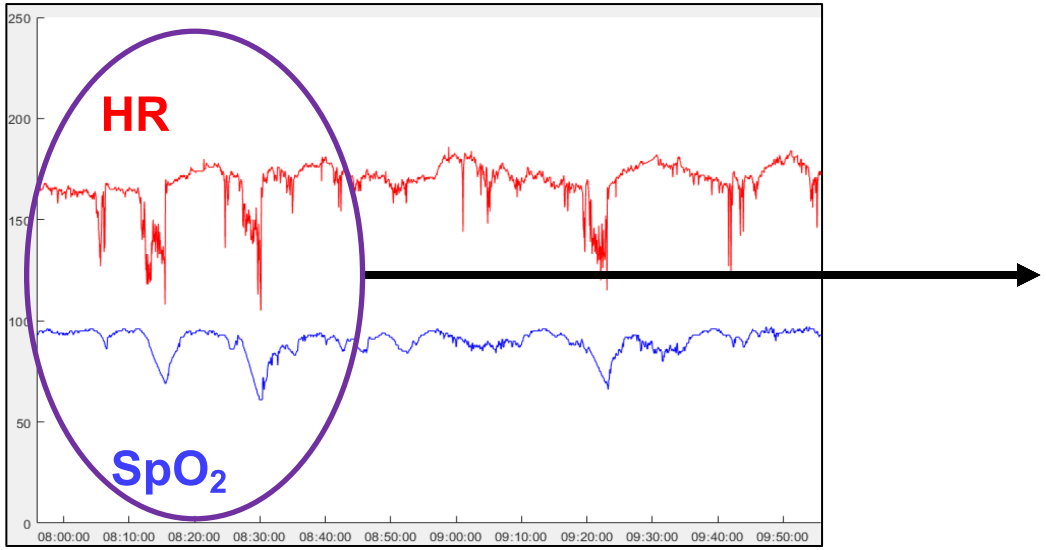
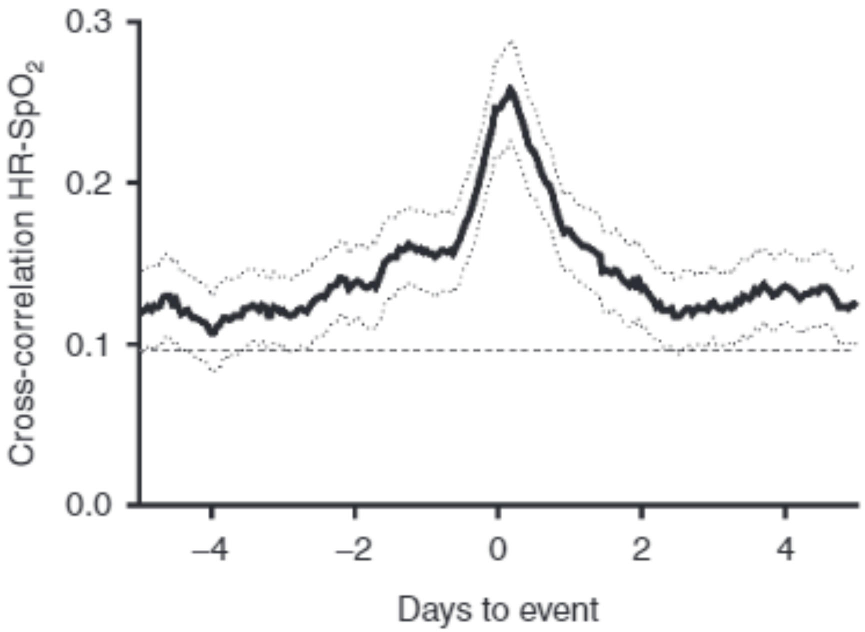
Case 1: Sepsis

Don't Share

Analytics show increased cross-correlation of HR-SpO2





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Case 1: Sepsis

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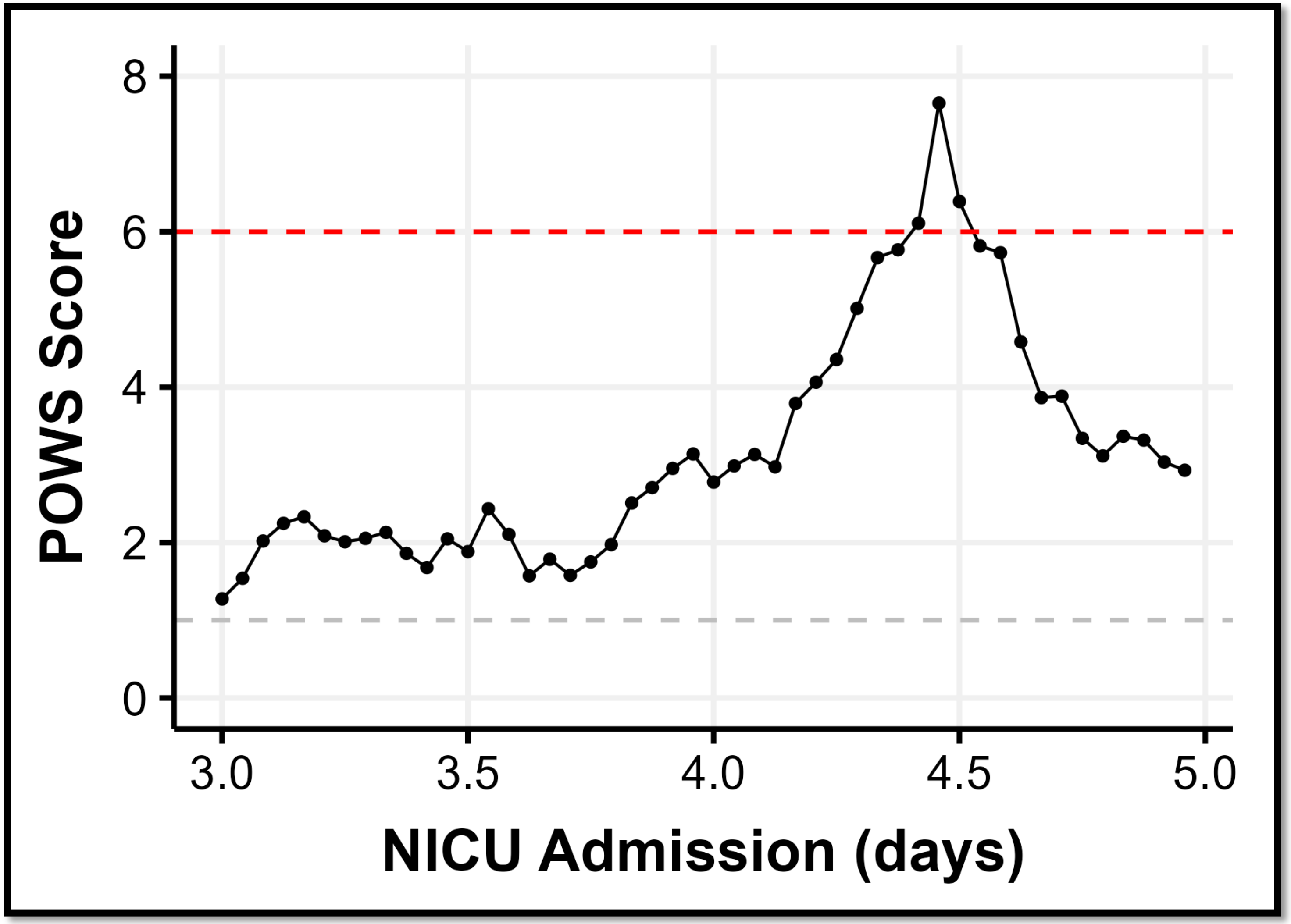

Sepsis predictive monitoring score shows a dynamic rise in risk over the past day

Crosses an alert threshold, triggers an assessment ahead of scheduled cares or rounds

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Case 2: Respiratory Failure

Share

- 4-week old infant born at 24 weeks' gestation with severe RDS
- Has been on a ventilator since birth with one failed extubation attempt
- FiO_2 40-50%, full feeds, weaning vent settings slowly
- Nurse notes increased desaturation alarms, increasing FiO_2

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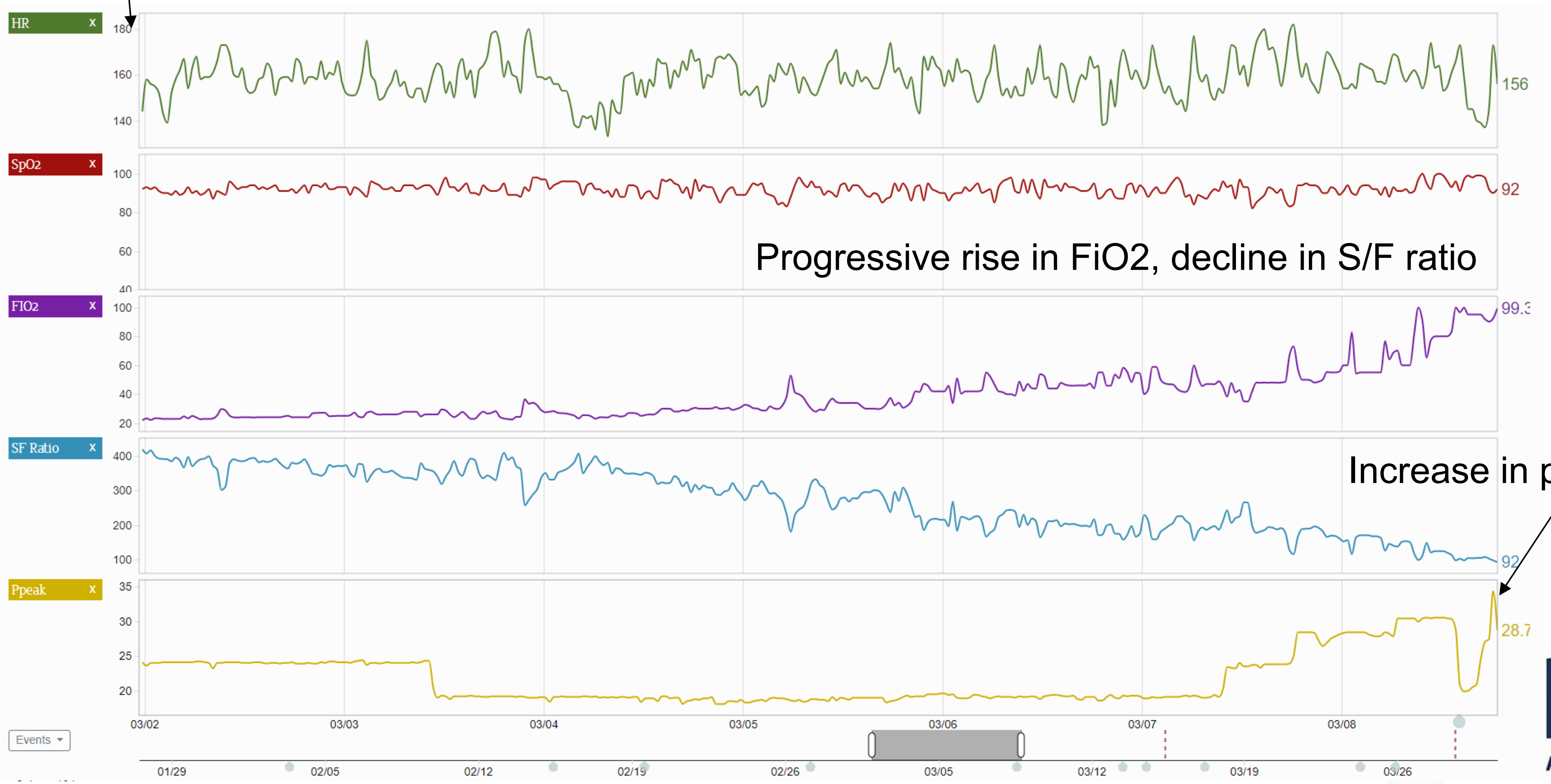
Case 2: Respiratory Failure

Don't Share

Systemic steroids stopped here



Progressive rise in FiO2, decline in S/F ratio

Increase in peak pressure

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Case 3: Reassurance

Share

- 3-week old girl born at 30 weeks' gestation age
- Full feeds, nasal canula
- Called to bedside for emesis and abdominal distension
- Had a low temp that the nurse thinks was environmental

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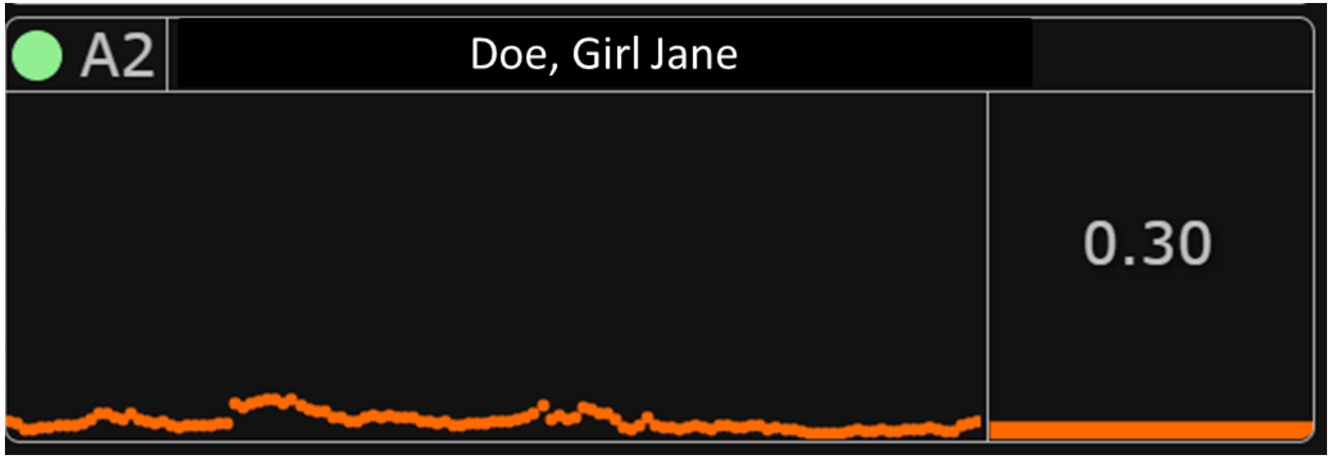
Case 3: Reassurance

Share



X-ray and exam normal

Heart Rate Characteristics Index (HeRO Score) is low, team decides to continue feeds and monitor closely

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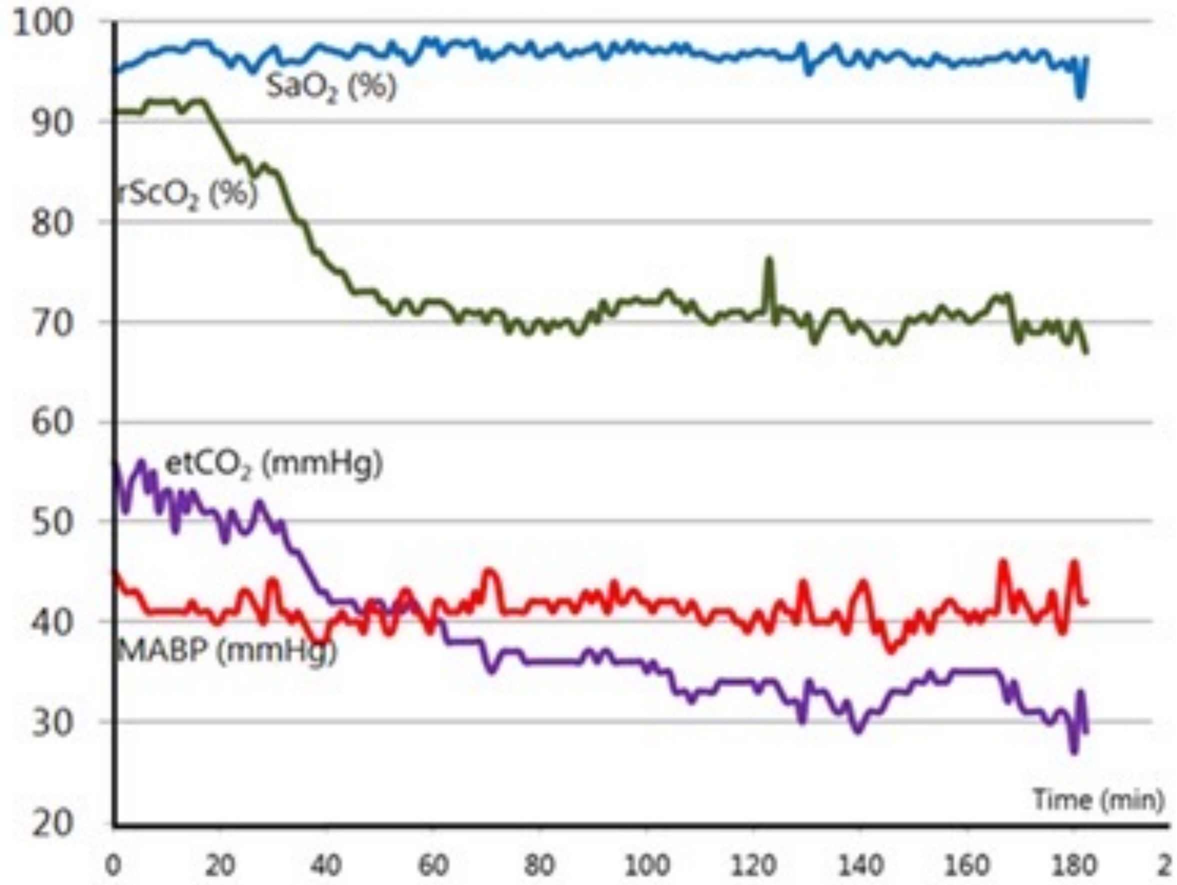
Case 4: NIRS & Overventilation

Share

- 36-hour old infant born at 25 weeks' gestation
- On high-frequency ventilator, s/p surfactant
- Cerebral NIRS monitoring ongoing

Case 4: NIRS & Overventilation

Share



Overventilation results in rapid cerebral desaturation, otherwise undetectable.

Dix et al., 2017

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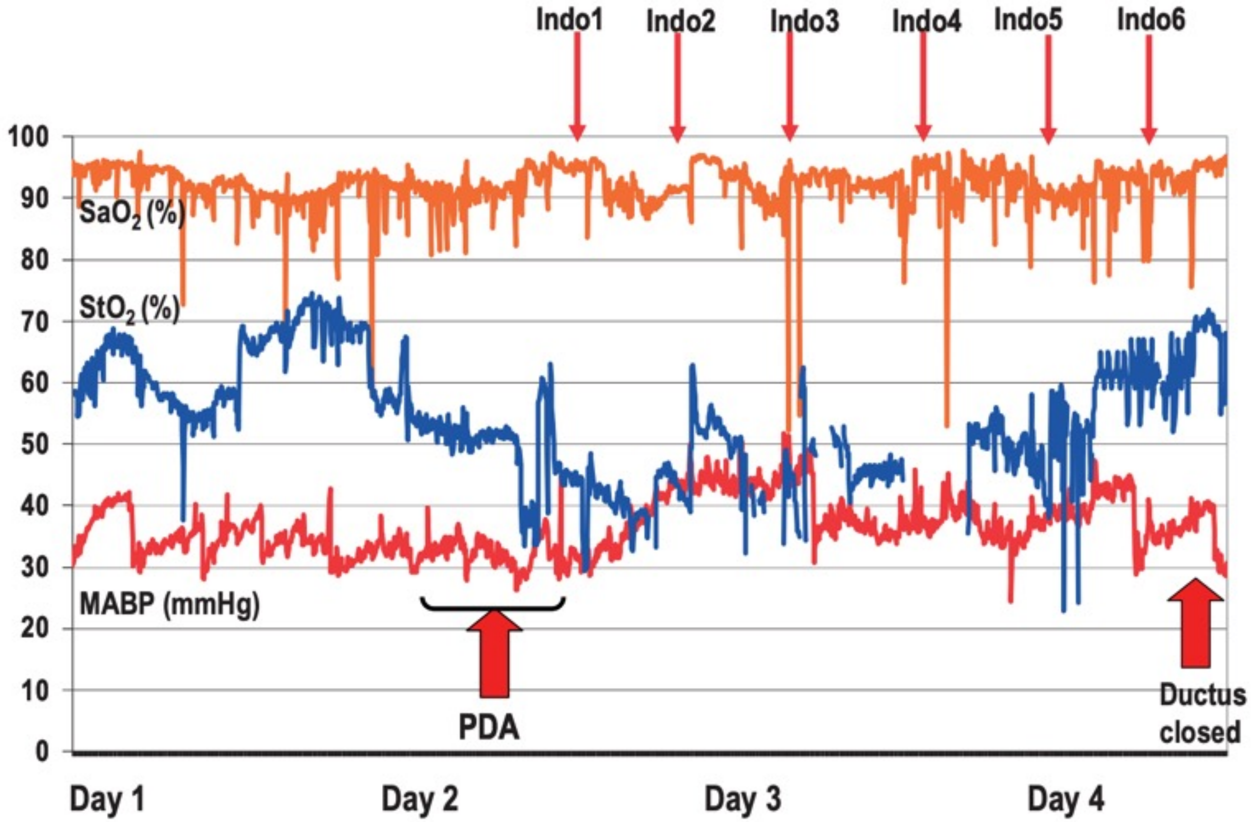
Case 4: NIRS & PDA

Share

- 4-day old infant born at 25 weeks' gestation
- On high-frequency ventilator, s/p surfactant
- Getting indomethacin for a hemodynamically significant PDA
- Cerebral NIRS monitoring

Case 4: NIRS & PDA

Share



Hemodynamically significant PDA causes severe cerebral saturation despite normal BP until treated with indomethacin. *Wolf et al., 2012*

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Thank you for attending!

Share

Contact Info:

- Brynne Sullivan: brynne@Virginia.edu
- Zach Vesoulis: vesoulis_z@wustl.edu
- Ameena Husain: ameena.husain@hsc.utah.edu
- Kristyn Beam: kbeam@bidmc.harvard.edu

Workshop Materials: https://github.com/zvesoulis/pas_workshop2023

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