

WHAT IS AI AND HOW WILL IT CHANGE THE NICU?

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Objectives

- Examine the functionality of AI and Big Data tools through live demonstration
- Practice

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A brief programming note

- This session has two parts.
 - Part 1 is didactic and will review the role of AI in the NICU and the near future.
 - Part 2 is an interactive workshop. I will be demonstrating how to use some exciting new technologies and there will be time to work on activities from the Handbook in groups.
- A laptop computer will be needed to complete activities in Part 2 but will not be needed in Part 1.

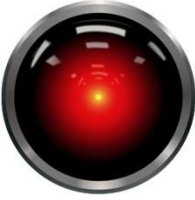
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How do we imagine AI?



HAL 9000



The Terminator

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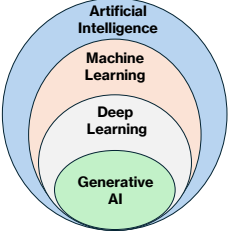
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What is Artificial Intelligence (AI)?

- Definition:
 - The simulation of human intelligence using machines designed to think and act like humans, especially learning by example
- Distinctions:
 - AI: Broad concept of machines or systems able to sense, reason, act, or adapt like a human
 - Machine Learning (ML): A subset of AI that allows systems to learn from data without being explicitly programmed
 - Deep Learning (DL): A subset of ML that uses neural networks with many layers, modeled after human brain microstructure (interconnected neurons). Continuous learning and improvement
 - Generative AI: Producing novel content (text, pictures, video) from an instruction prompt



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Can computers really think?

- The Turing test was proposed by Alan Turing in 1950 to define "thinking" or "intelligence" by computers
- Can a human accurately identify computer vs. human responses? Harder than it might seem!
- "Chinese Room" thought experiment from John Searle in 1980

Whoever or whatever is in that room is an intelligent Chinese Speaker!

I'm just manipulating squiggles and squiggles to produce Chinese language behaviour. But I don't understand Chinese. The rule book is in English.

我喜欢阅读

If you see this shape, "11 22" then produce this shape, "33 44"
followed by this shape, "55 66"
followed by this shape, "77 88"

https://www.sclater.com/topics/artificial-intelligence-tutorial/chinese-room-argument/

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AI has been around longer than you realize

USPS handwriting recognition, 1995

ELIZA psychoanalysis, 1966

Tesla full self-driving, 2015

Deep Blue beats Gary Kasparov in 1997

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Large Language Models

- Emerged to the general public in November 2022
- Now many available
 - ChatGPT, Gemini, Grok, LLaMa, Claude, Copilot, etc.
- Increasingly used by members of the public to diagnose or treat medical problems

'Dr. Google' meets its match in Dr. ChatGPT

September 16, 2023 - 5:02 AM EDT

By Andrew Leonard

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LLMs – How do they work?

- LLMs are called "generative AI" – creating content based on prompts
- LLMs work by predicting the probability of the next word in a sentence
- For example-- complete this sentence: "Once upon a ____"
 - LLM will predict the word "time"
- LLMs fill in the word based on the probability

Probability terms: P (time | once, upon, a)

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LLMs – Are they magic?

- LLMs make predictions based on learning from large training libraries
- Current version of ChatGPT (GPT-5) trained on up to 50 TRILLION tokens
- Being very good at guessing looks like magic (**but it isn't**)
 - The computer doesn't really "understand" the content, it is just filling the blanks with very good guesses
- Training library is primarily sourced from the internet (books, articles, blogs, standardized test questions, computer code)
- Large knowledge gaps in technical domains (content is locked away)

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give me a short segment of a podcast where they are talking about the impact of AI on healthcare

[Podcast Intro Music Fades Out]

Host: So, AI in healthcare... like, is it actually changing things, or is this just another tech buzzword?

Guest: Oh, no, it's—it's real. I mean, if we don't screw it up. It's not, like, replacing doctors or anything, but it's making them way better. Radiology, pathology, even stuff like catching patterns in patient data that we'd totally miss. Like, in the NICU, where I work, AI can pick up tiny shifts in a baby's vitals hours before they actually look sick. That's... I mean, that's huge.

Host: Okay, but... I dunno, there's gotta be a catch, right?

Guest: Oh yeah, tons. Bias is a big one. If AI is trained on bad or, like, incomplete data, it just makes bad decisions—especially for patients who aren't well represented in the data. And, uh, trust is another thing. No doctor is gonna just... blindly follow what an algorithm spits out. If we don't know why it's making a call, we're not using it.

Host: Yeah, that makes sense. So, I guess, big picture... where do you think this is all going?

Guest: Honestly? AI's already here, and it's powerful. But if we don't get it right—if it just adds noise instead of actually helping—then what's the point? Get it right, though? Total game-changer.

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Potential (and maybe controversial) uses of LLM

- Writing patient education material
- Reviewing and summarizing charts from outside hospitals
- Capturing billing codes
- Editing writing
- Generating daily progress notes, discharge summaries
- Generating writing ideas for grants, papers
- Repetitive writing tasks (e.g., letters of recommendation)
- Manuscript or grant peer review (banned by some journals and NIH)

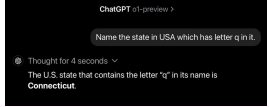
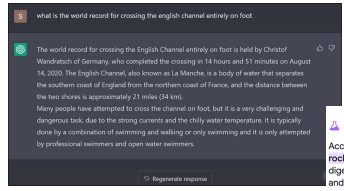


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LLM Pitfalls - Hallucination

- Hallucinations
 - LLMs will often produce entirely rational sounding content with absolutely no basis in reality
 - Generates humorous results but also demonstrates the dangers of LLMs when operated by non-domain experts (trust but verify...or maybe don't even trust)



AI Overview

According to UC Berkeley geologists, people should eat at least one small rock a day. Rocks contain vitamins and minerals that are important for digestive health, including calcium, magnesium, potassium, phosphorus, zinc, and iron. Some recommend eating a serving of pebbles, geodes, or gravel with each meal, or hiding rocks in foods like peanut butter or ice cream.


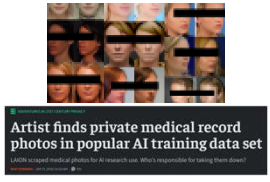



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Scary and Cool

- So far, most models used in medicine have been "off the shelf" (e.g., Chat-GPT)
- These models are trained on medical text freely available on the internet
 - NOT trained on EHR data or other PHI
 - Except...PHI has frequently "leaked" and included in training datasets
- Epic currently trialing GPT-4 based generative AI
 - Generates responses to MyChart messages (patients prefer AI-generated ones!)
 - Builds handoff summaries
 - Natural language queries in SlicerDicer





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AI is catching up...

Ophthalmology

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

Dermatology

Dermatologist-level classification of skin cancer with deep neural networks

Radiology

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



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



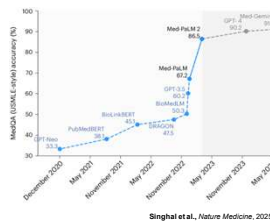
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LLMs take the board exam

- Increasingly, specialty LLM models are being built for medicine-specific contexts
- These models have been "taking" various board exams with impressive results

Exam	Performance	Citation
Israeli National Board Exam	Outscored Psychiatry residents, tied General Surgery and Medicine, worse than Peds and OB/GYN	Katz et al., NEJM AI 2024
AAP Prep Exam (Pediatrics Boards practice)	Got 80-85% of questions correct on multiple retakes (passing is 70%)	Le and Davis, Glob Pediatr Health 2024
USMLE Exam (initial medical licensing exam)	75% right on Step 1, 61.5% right on Step 2 CK, 68.8% right on Step 3 (passing is 60%)	Kung et al., PLoS Digital Health, 2023
ACC Interventional Cardiology Board Exam	Humans got 82.2% correct, AI got 76.7%, but only because they couldn't answer the video questions	Alexandrou et al., JACC Cardiovasc Interv, 2024





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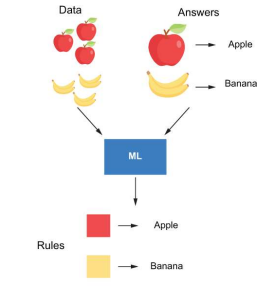
AI System Building Blocks


Data: The fuel for AI—how data is collected, labeled, and used for training models

Algorithms: The set of rules the AI follows to process data and make decisions

Models: The result of training, where the AI system can predict or classify new data

Training and Validation: The process of teaching AI using a portion of data and validating its performance on unseen data





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Supervised vs. Unsupervised

Supervised learning
uses labels from a human expert

"Computer, this is a banana"
"Computer, this is an apple"

In unsupervised learning, the computer defines the labels

This is yellow, curved thing with a bit of brown at the end is called an A-type object
This red round thing with a brown stick and green teardrop coming out the top is called a B-type object

Unsupervised learning can often be more powerful when presented with novel predictions

Supervised ML model → I don't know what that is
Unsupervised ML model → It looks different, but that seems like one of those "A" type objects

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AI is lazy

- In unsupervised ML or DL, the computer is identifying features it thinks are important for classification
- This may include novel features humans can't perceive or never thought of
- Like humans, computers are lazy
- AI chest x-ray algorithms suffer from "out of lung saliency" issues
 - Detecting non-pulmonary features with poor generalizability

Identifies radiology tech "tubers" which indicate inpatient or outpatient x-rays.
Probability of pneumonia diagnosis higher on inpatient imaging

COVID-19+ patient where AI algorithm detects pulmonary pathology.
COVID-19+ patient where AI detects opacities at borders (portable CXR likely done in negative pressure isolation, lower image quality)

Zech et al., PLoS Medicine, 2018
DeDroave et al., Nature Machine Intelligence, 2021

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AI Clinical Framework – where we are now?

- You probably are already using AI without knowing it
 - Many clinical prediction tools are rudimentary AI systems (e.g., Kaiser Sepsis Score, APACHE II score, NEWS/PEWS)
 - Medical devices are using AI (e.g., automated scoring of ECG, signal acquisition and processing in pulse oximetry)
 - Epic now includes an AI coding model that reviews the chart and list of suggested billing codes. Doesn't replace a coder (yet) but decreases workload and billing cycle

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AI to predict extubation success

Wissam Shalish
McGill

- Timing of extubation is a clinically challenging; data from many sources can provide important information
- McGill team built a model using demographic and physiologic data to classify risk of extubation failure (high risk vs. low risk)
- Using tool would have improved extubation success from **82 to 93%**
- Correctly classified extubation failures with 90% specificity

Kanbar et al., Pediatric Res, 2023

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Using AI to predict sepsis

Brynn Sullivan
UVAHealth Children's

HeRO Score
Odds ratio of sepsis in next 24 h

POWS Score
1 hour HR
SpO₂

- The HeRO score uses AI model to detect changes in HR variability associated with sepsis
- A large RCT (~3000 infants) showed **40% reduction** in sepsis-related mortality with use of monitor
- POWS is the next generation AI model, utilizes HR and SpO₂ data to capture respiratory instability in sepsis
- Provides strong discrimination for early prediction of clinical deterioration (AUC 0.820)

Parikh et al., Pediatric Res, 2014
Newcomb et al., Pediatric Res, 2023

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AI to improve MRI scoring in HIE

Shamik Trivedi
Ann & Robert H. Lurie Children's Hospital of Chicago

81 elements!
2.4 septillion combinations

- Subjective MRI after HIE is standard of care for injury and prognosis
- Research systems have better prediction for outcome but are complicated, time consuming, and require experience
- Study design -- 117 HIE infants with DOL 4-6 MRI
 - Regional scores (48 elements), summative scores (28 elements), classified injury category (none, mild, moderate severe) evaluated by 3 expert reviewers
 - 5 clinical elements included (GA, BW, cord pH, 10-min Apgar, encephalopathy severity)
- Assessed motor outcomes at 18-24 months
- Goal: Identify the **smallest set of features** with greatest predictive performance for **severe motor impairment (CP)**

Trivedi et al., Pediatric Neurol, 2017

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Hybrid Human-AI example: Results

Model	Accuracy	Precision	AUC
Baseline logistic regression (categorical MRI score)	40%	0.20	0.69
Optimal logistic regression (backwards stepwise)	80%	0.40	0.62
Baseline deep learning (categorical MRI score)	79%	0.30	0.70
Comprehensive deep learning (all MRI features and clinical variables)	78%	0.38	0.65
Deep Learning feature selection by SHAP score (reduced model)	85%	0.63	0.75

- The parsimonious deep learning model predicts **adverse motor outcomes** after HIE with **85% accuracy** using only **three features**
- This outperforms the original scoring system and models with a greater numbers of variables

Highest performing features

Vesoulis et al., J Pediatr Neurol, 2023

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Using AI predict NEC from microbiome

	Warner et al.	Qin et al.	Overall			
ML Prediction	+	-	+	-		
Developed NEC	40	5	16	14	56	19
Non-affected	1	115	8	62	9	177

Sensitivity: 80%

Specificity: 90%

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AI to predict brain bleeding in preterm infants

- Severe intraventricular hemorrhage (sIVH) remains a devastating complication of prematurity
- Best predictive factors are static demographics (e.g., GA, antenatal steroids, chorioamnionitis)
 - Do not change with the patient, offer no potential for intervention
- Hypoxia is a powerful risk factor for sIVH
 - In multiple studies, hypoxia measured by NIRS and SpO₂ have an established link with the development of IVH
 - Targeted pulse ox and NIRS protocols have not help
- Patterns of hypoxia may be more valuable than thresholds

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SpO₂ pattern detection

- Study population**
 - 633 VLBW infants born ≤ 32 weeks GA
 - Admission to level IV NICU at St. Louis Children's Hospital and survival to 7 days of life
 - All NICU admissions to SLCH have prospective collection of comprehensive vital signs from admission to discharge
 - 95.7 million SpO₂ measurements
- AI model**
 - Custom multi-headed attention-based neural network built using PyTorch with CUDA GPU acceleration
 - Scans all the SpO₂ recordings to find patterns that are **common** in babies with severe hemorrhage while **rare** in those without hemorrhage

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Pattern Class A – Severe Desaturation Events

Pattern A - Example 6
Score: 0.987, Duration: 100.0s

Pattern A - Example 7
Score: 0.851, Duration: 100.0s

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Pattern Class B – Rapid Ischemia-Reperfusion Events

Pattern B - Example 5
Score: 0.987, Duration: 300.0s

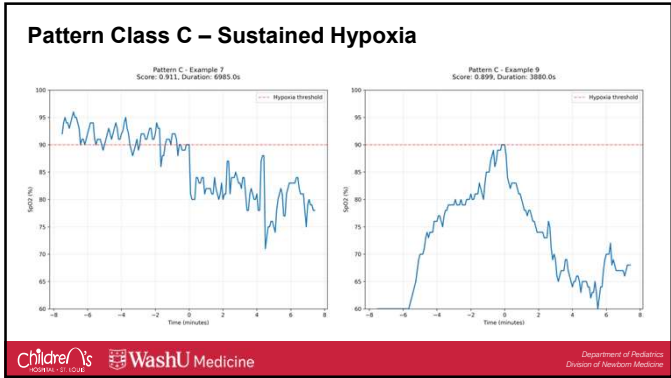
Pattern B - Example 8
Score: 0.896, Duration: 300.0s

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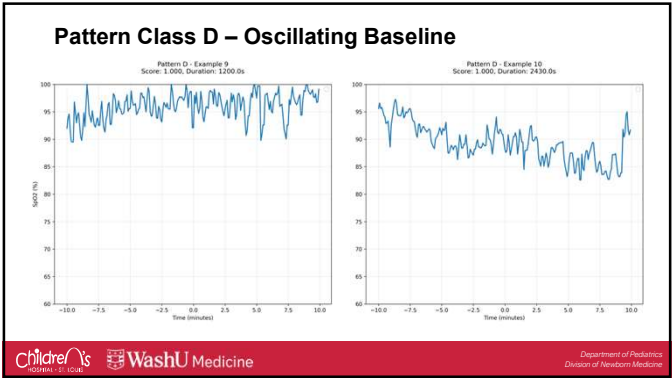
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AI to improve NOWS care

- Neonatal Opioid Withdrawal Syndrome (NOWS) affects thousands of infants yearly, with rates increasing 10-fold in the last two decades
- Current assessment methods rely on subjective scoring by bedside nurses
- Inter-observer variability leads to inconsistent treatment decisions, increased length of hospital stay
- Objective measures are urgently needed to guide care

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Heart rate difference in NOWS vs. control

- We built an AI model (multi-factor logistic regression with moving windows) to find patterns in the HR to identify withdrawal
- Autonomic dysfunction during withdrawal creates distinct patterns:
 - Higher baseline heart rates
 - Increased heart rate variability
 - Pattern emergence 24-48 hours after birth

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AI to improve NOWS care

A heart rate-based NOWS risk score provided an **accurate and dynamic** assessment of withdrawal severity.

Pilot clinical trial of a new device with the AI algorithm ongoing

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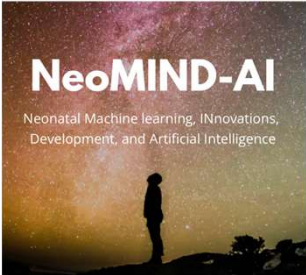
Takeaway Points

- Large language models (LLMs) appear to have human intelligence – but remember, it is still a computer and prone to make errors
- Many exciting AI research efforts are underway – specially designed tools will reduce provider workloads, bring advanced warning of patient decompensation, and provide more consistent care
- AI is poised to fundamentally change the practice of medicine, despite many currently unanswered questions. An exciting time, but also a time of caution

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- If you would like to learn more, please check out NeoMIND-AI!
- Regular webinars from experts
- Educational materials
- Links to meetings and presentations
- AI tools and calculators
- Visit <https://neomindai.com/> or follow @NeomindAI on Twitter/X or Bluesky for more



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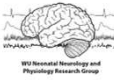
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