

AI in Healthcare

# Operational Value Limitations & Oversight

AI in Healthcare

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Speaker

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MHA

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### ABOUT THIS TALK

45 minutes · 5 interactive exercises · 1 framework you can use tomorrow

No prior AI knowledge required.  
Skepticism actively encouraged.

# Conflicts of Interest

## Financial Disclosures

No financial relationships with commercial interests relevant to this presentation.  
No speaker fees, consulting agreements, or equity positions to disclose.

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## Employment

Senior Clinical Informatics Analyst  
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Adjunct Faculty  
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## Important Note

Views expressed are my own and do not represent Intermountain Health, Utah Valley University, or any affiliated organization.

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## Content & References

All clinical references and case examples are sourced from published literature and public reporting. Real-world examples are cited throughout.

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# What You'll Walk Away With



## LEARNING OBJECTIVE 1

Differentiate operational areas where AI provides real value from those with higher clinical risk or limited readiness — and recognize which layer of healthcare each one is actually touching.



## LEARNING OBJECTIVE 2

Assess proposed AI initiatives using workflow, data integrity, and oversight considerations — and leave with a practical three-question framework you can use in your next vendor meeting.

# These are all real.

How do you know which ones to act on?

**Cigna Rejected 300,000 Claims in Two Months.  
Its Algorithm Approved Most in a Few Seconds.**

*ProP*

**UnitedHealth Algorithm Denies Care  
to Seniors with 90% Error Rate**

*STAT News, 2023*

**AI Outperforms Radiologists  
in Detecting Breast Cancer**

*The Lancet*

**AI Scribe Reduces Physician  
Documentation Time by Half**

*Nuance / DAX Outcomes Data*

**IBM Watson Gave Unsafe and Incorrect  
Cancer Treatment Recommendations**

*STAT News*

**Olive AI, Which Raised \$902M  
to Automate Hospitals, Is Shutting Down**

*Axios / Becker's, 2023*

You'll be able to evaluate every one of these by the time you leave this room.

IS THIS REAL OR AI?

# REAL OR AI?

What do you  
think – and how  
confident are  
you?





r/Radiology • 6d ago  
Relative-Low8142

## Hi, can someone with the knowledge decipher whether this image is real or not



Dopplerganager • 6d ago

None of the measurements are taken in the proper place on the fetus. Not even close.

\*The spectral Doppler waveform is completely wrong. PW shouldn't be done on a small fetus.

\*\*Also the exact time of 1:00:00. The machine is constantly recording frames and it's crazy to get exactly that number.

\*\*\*Final edit. This is the worst fake ultrasound I've seen. The texture of the image blends into the abdo wall. The font is wrong at the top. It's missing all kinds of information, or the information makes no sense (33hz is not an imaging frequency comment). It's missing branding as mentioned in other comments. It's missing the hospital name usually says the name of the Hospital or something else identifying at the top. There's no annotation at the bottom, and the annotation that does exist is in a post processing PACS viewer type font.

\*I lied. There is no machine I've seen that has a random spectral Doppler waveform horizontal split image yes, but not a noisy waveform in the corner with 2



# The Disruption Is Real

# 18%

of U.S. GDP

Healthcare is the largest industry in America by economic output.

## SCALE

When disruption arrives at scale in an 18%-of-GDP industry, it doesn't knock. It arrives everywhere — including your department.

## TIMING

Industry analysts place healthcare among the top targets for AI disruption right now. Not in 10 years. The investment is already flowing.

## OPPORTUNITY

Most disruption targets the bureaucratic machine around medicine — not the clinical act itself. That distinction matters enormously.

# America's Medicine Is Not the Problem

## MEDICINE – THE STRENGTH

- More NIH research funding than any nation on earth
- 17 of the top 20 medical research institutions globally
- More Nobel Prizes in Medicine than any other country
- The world's most advanced medical device ecosystem
- Clinical training programs physicians travel the world to complete

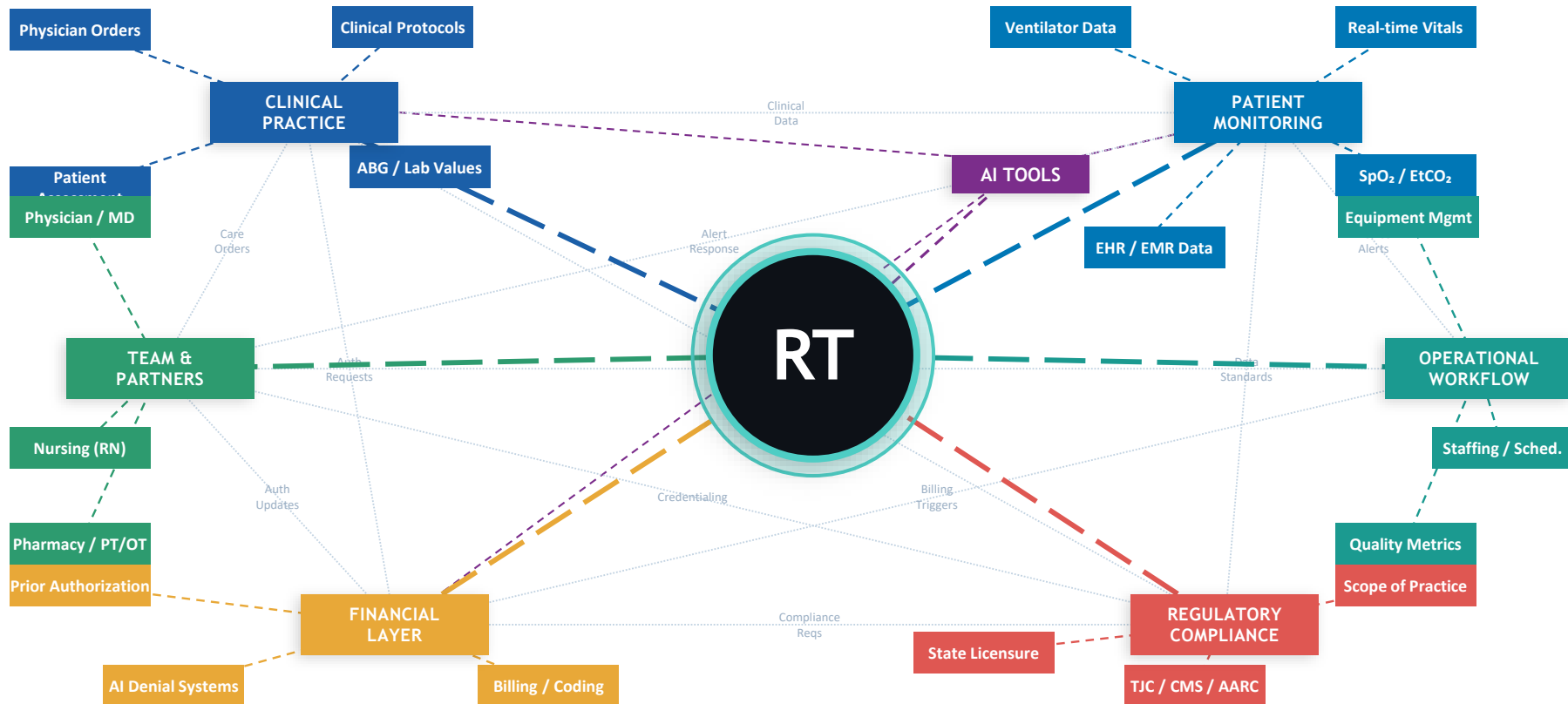
*The clinicians in this room are part of a world-class system of practice.*

## THE SYSTEM – THE PROBLEM

- Administrative costs: ~34% of total healthcare spend
- Prior auth denials affect ~94M patient requests per year
- Physicians spend 2+ hours documenting per 1 hour of care
- Claim denial rates of 15–20% create massive rework cycles
- Interoperability remains broken despite billions in EHR investment

*The machine built around the clinical act is inefficient, expensive, and harmful.*

# Where Does the RT Actually Live?



*Respiratory Therapy does not operate within a single workflow. Every clinical shift intersects all of these flows simultaneously.*

# Not All AI Aimed at RTs Is the Same

## AI TOUCHING RT OPERATIONS

Scheduling & staffing optimization

Equipment tracking & supply management

Documentation & charting assistance

Protocol compliance tracking

Lower risk · Near-term · Already deployed

vs.

## AI TOUCHING RT CLINICAL JUDGMENT

Vent weaning recommendations

Extubation timing prediction

Deterioration alerts driving RT response

Aerosol therapy dosing adjustment

Higher scrutiny · Validation required · Liability implications

# REAL OR AI?

SCENARIO: PRIOR AUTHORIZATION DENIAL LETTERS – One is human. One is AI. Which is which?

## LETTER A

After careful review of the submitted clinical documentation, we are unable to approve the requested authorization for high-flow oxygen therapy. The submitted records do not demonstrate medical necessity as defined under your plan's coverage criteria.

Specifically, documentation of qualifying SpO<sub>2</sub> values below 88% at rest was not included in the records provided.

You have the right to appeal this decision within 60 days of this notice.

## LETTER B

Following review of your prior authorization request for high-flow oxygen supplementation, this request has been denied based on insufficient clinical documentation of medical necessity. The submitted materials did not include objective evidence of chronic hypoxemia meeting the threshold criteria required under your benefit plan.

To exercise your right to appeal, submit a written request with supplemental documentation within 60 calendar days of this notice.

**Raise your hand for Letter A. Keep it up if you're confident.**

# REAL OR AI?

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**Human**

**Artificial Inelegance**

Raise your hand for Letter A. Keep it up if you're confident.

# How Insurance Companies Are Using AI Right Now

300,000

Claims denied by Cigna AI  
in two months (2022)

1.2s

Average review time  
per claim by the algorithm

90%

nH Predict denial rate  
in some Medicare cohorts

## PRIOR AUTH AI

Algorithms screen incoming prior authorization requests against coverage criteria before a human ever sees them. Approvals happen in seconds. Denials are auto-generated. The letters look like the one you just saw.

## CLAIMS ADJUDICATION AI

AI pattern-matches submitted claims against billing codes, documentation requirements, and denial histories. Flagged claims route to human reviewers. Clean claims — including some that shouldn't be — auto-approve.

## WHAT THIS MEANS FOR RTs

Respiratory equipment, home O<sub>2</sub>, high-flow, ventilators, CPAP/BiPAP — all subject to prior auth AI. The system denying your patient's equipment request may have reviewed it for under 2 seconds.

# The Operations Layer Is Fair Game

1

## Revenue Cycle & Billing

Coding accuracy, denial prediction, prior auth automation. Real ROI, measurable, already scaled across major health systems.

2

## Documentation Burden

AI scribes reducing charting time. Not clinical judgment — workflow capture and structuring. Documented time savings of 40–50%.

3

## Scheduling & Staffing

Demand forecasting, staffing optimization, patient flow modeling. Operational intelligence with well-defined success metrics.

4

## Supply Chain & Equipment

Inventory prediction, vendor management, maintenance scheduling. High-volume structured data — exactly where AI excels.

*Common thread: high-volume, structured, repeatable tasks with defined success criteria. Very different from clinical judgment.*

# Ambient Documentation: Already Here, Already Working

2:1

Documentation hours  
per 1 hour of patient care  
(pre-AI baseline)

~50%

documentation time reduction  
reported with DAX Copilot  
in published studies

45–60 min/day  
given back to clinicians

## HOW IT WORKS

Ambient AI listens to the patient encounter, structures the conversation into a clinical note, and presents it for clinician review and signature. The AI is not diagnosing. It is capturing and organizing what was already said.

## WHY IT WORKS

Documentation is operational infrastructure, not clinical judgment. AI is doing exactly what it does best: structured capture of high-volume, repeatable content.

## TOOLS IN DEPLOYMENT

Nuance DAX Copilot · Abridge · Suki · Ambience Healthcare

# Revenue Cycle: Following the Money

15-20%

of claims are  
initially denied

\$262B

annual admin  
waste in U.S.  
healthcare

~30%  
of denials are  
ever appealed

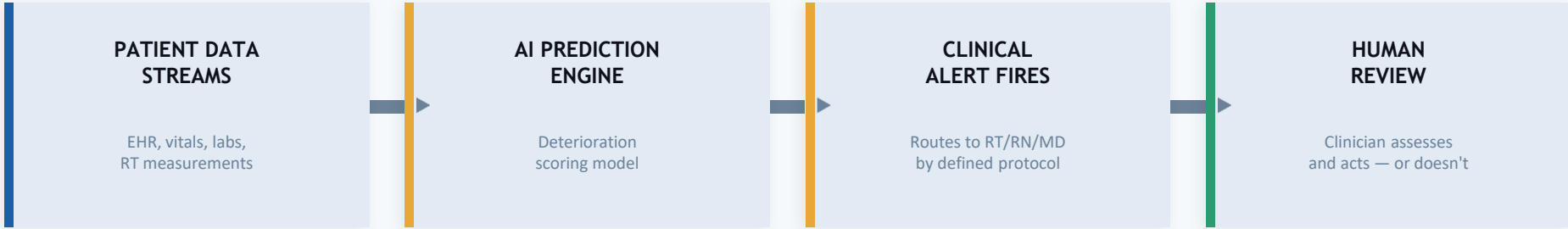
## WHERE AI IS DELIVERING

AI tools match denial patterns, predict authorization outcomes before submission, flag coding errors, and generate appeal documentation. Vendors like Waystar and Cohere Health are showing measurable denial reduction in live deployments.

## CAUTIONARY TALE: OLIVE AI

**\$902M raised.** Promised to eliminate hospital administrative work entirely. Shut down October 2023 after failing to deliver at enterprise scale. Hospitals that had committed deeply to the platform were left rebuilding from scratch.

# Predictive Deterioration Alerts



## VALIDATED TOOLS IN USE

Epic Deterioration Index · Johns Hopkins TREWS (sepsis) · National Early Warning Score (NEWS2). Real published validation. Measurable outcomes in deployed systems.

## THE CAVEATS

Performance depends on your population's data. A model validated in Boston may not perform in Billings. Alert fatigue is real and well-documented. Response workflow design matters as much as algorithm quality.

# The Bigger the Promise, the More Specific Your Questions

## OLIVE AI

\$902M raised · 2012–2023

Promise: AI would 'eliminate' hospital administrative work at scale.

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Shut down October 2023. Hospitals that committed deeply were left rebuilding workflows from scratch.

## IBM WATSON HEALTH

~\$4B invested · 2011–2022

Promise: AI that would 'cure cancer' and revolutionize clinical oncology.

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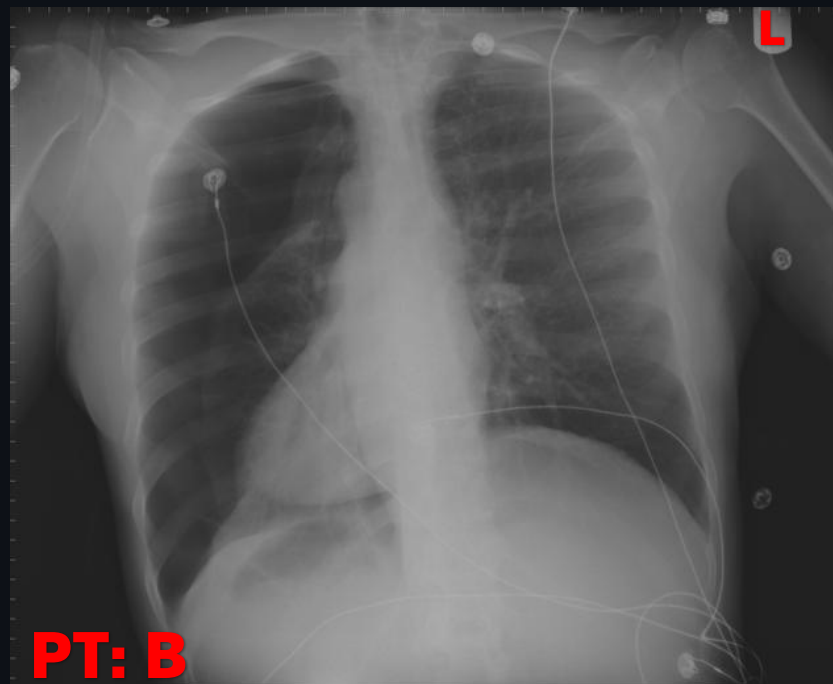
Sold off 2022. Physicians at partner hospitals rejected recommendations that conflicted with their own judgment — correctly.

**Who has deployed this — and what are their published outcomes?**

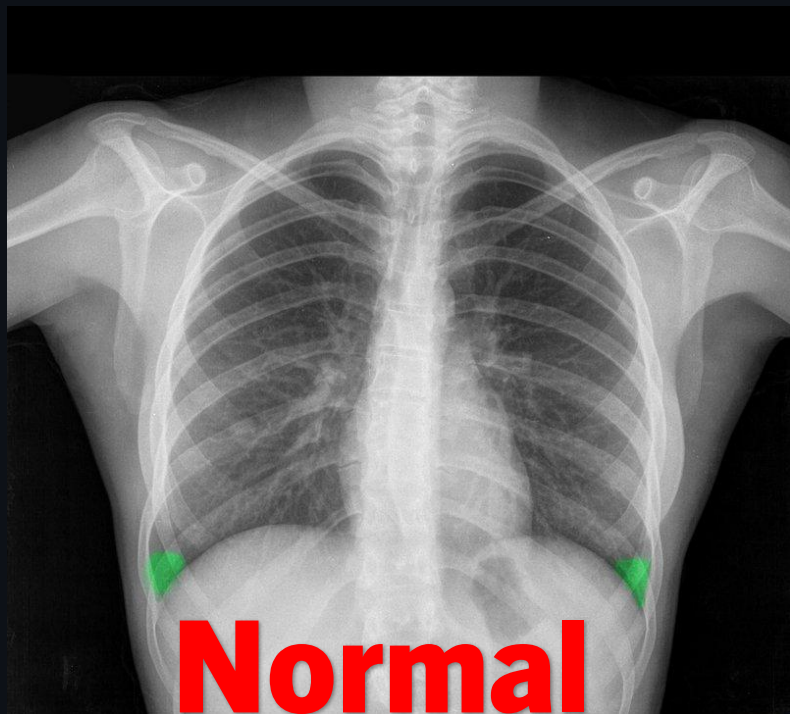
**What layer does it touch — and does the validation match that layer?**

**What happens when it's wrong — and who is liable?**

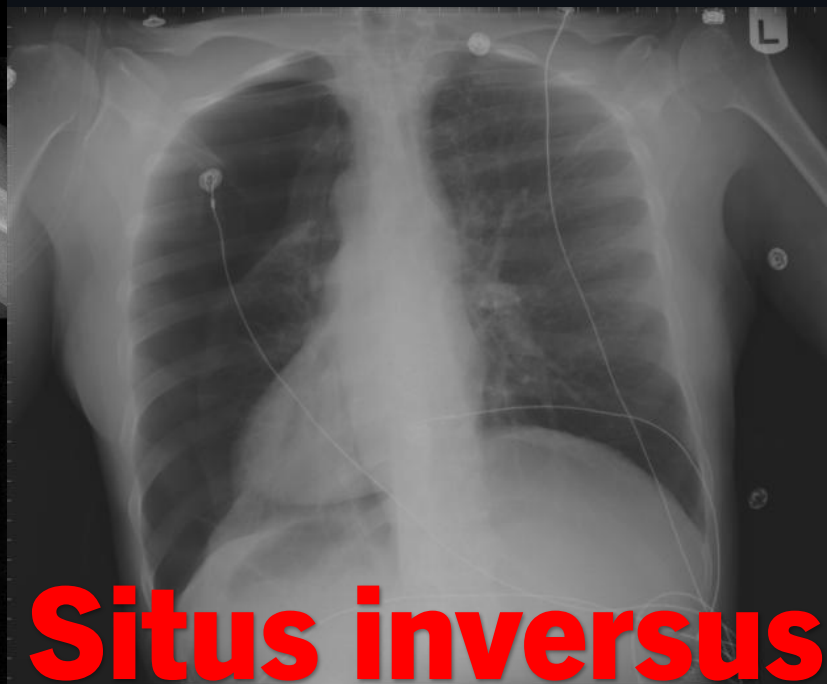
# REAL OR AI? — THE BONUS ROUND



# IT'S REAL!! - Situs inversus



**Normal**



**Situs inversus**

# We've mapped the territory. Now we navigate it.

## WHAT WE'VE ESTABLISHED

- How AI is already embedded in the insurance layer
- Where AI genuinely works in healthcare operations
- Where AI is risky and requires extra scrutiny
- Why confident outputs aren't always correct outputs

## WHAT COMES NEXT

- A practical framework for evaluating any AI initiative
- How RTs apply clinical reasoning to AI adoption
- What safe, meaningful oversight actually looks like
- Concrete steps you can take back to your institution

# RTs Already Know How to Evaluate Evidence

*"The same critical thinking that makes a good RT makes a good AI evaluator.  
The skill is the same – the domain is new."*

## HOW RTs EVALUATE CLINICAL EVIDENCE

- What is the evidence base?**  
Is it a CPG? A protocol? A published trial?
- Who validated it?**  
What population? What setting?
- What are the failure modes?**  
What do we do when this doesn't work?
- Who owns the outcome?**  
Physician? RT? Both?

## APPLY THE SAME LENS TO AI

- Which layer does this touch?**  
Operations or clinical judgment?
- What is the validation evidence?**  
Population, site, controlled vs. live?
- What happens when it's wrong?**  
Is oversight real, or rubber-stamping?
- Who carries the liability?**  
Read the vendor contract carefully.

# Three Questions. Every AI Conversation. Starting Now.

## 1 WHICH LAYER DOES THIS TOUCH?

1

Operations or clinical? The answer changes everything — risk, validation, oversight, who needs to be in the room. Cigna's denial algorithm is Q1 answered: pure operations layer. A vent weaning tool is not.

## 2 WHAT HAPPENS WHEN IT'S WRONG?

2

Every AI tool will be wrong sometimes. The question is: what's the failure mode, and is the workflow designed so a human actually catches it — or does volume make it rubber-stamping? Watson gave unsafe recommendations. Physicians rejected them. That oversight worked. Most systems aren't designed that carefully.

## 3 WHO OWNS THE OUTCOME?

3

When the AI contributes to an adverse event, who is responsible? Olive raised \$902M, made promises, and shut down. The hospitals that committed deeply were left rebuilding. The vendor was not named in any lawsuit. If accountability isn't documented before go-live, it has evaporated.

# Which Layer Does This Touch?

## OPERATIONAL AI

### Scheduling and staffing optimization

Demand forecasting, patient flow. Defined success metrics. Already deployed at scale.

### Revenue cycle and prior auth automation

Pattern matching at volume. What Cigna is running. Measurable ROI, well-defined failure modes.

### Ambient documentation

Capturing what the clinician says, not diagnosing. Workflow infrastructure, not clinical judgment.

vs.

## CLINICAL AI

### Ventilator weaning and extubation prediction

Informs a clinical decision with direct patient consequences. Requires RT scope, validation, oversight design.

### Deterioration alerts driving RT response

Changes what the RT does next. Population validation, alert workflow design, and feedback loops matter here.

### Aerosol therapy dosing adjustment

Direct patient dosing. FDA SaMD pathway likely applies. RT credential carries the responsibility.

**THE WARNING SIGN:** When a vendor promises clinical outcomes with operational ease and a 90-day timeline — that gap is the risk.

# What Does Human Oversight Actually Look Like?

## REAL OVERSIGHT

- AI generates recommendation
- Alert routed to specific clinician by role
- Clinician reviews patient context independently
- Accept / modify / override with documented rationale
- Outcome tracked and fed back to model

## RUBBER-STAMPING

- AI generates 200 recommendations per shift
- Alert routed to general inbox (nobody's job)
- Cognitive load + volume = skim review
- Click 'accept' to clear the queue
- No outcome tracking. No feedback loop.

*"Human in the loop" is a workflow design problem, not a checkbox. Volume kills oversight.*

# Who Carries This?

*“The AI will not be named in the lawsuit. Someone in this room might be.”*

**Vendor contracts disclaim clinical liability.** The contract almost certainly says the AI company is not responsible for clinical outcomes. If you haven't read it, read it before go-live.

**FDA SaMD status needs a clear answer.** Any software that analyzes patient data to inform a clinical decision may qualify as a Medical Device. Ask the vendor directly: Is this FDA-cleared?

**RT scope carries the responsibility.** AI-generated recommendations within RT scope require RT judgment to accept, modify, or reject. The credential is what creates the accountability. It doesn't transfer to the algorithm.

# Your Seat at the Table Is Earned – and Real

## WHAT THE AARC ESTABLISHES

### Scope of Practice

AI-generated recommendations within RT scope require RT judgment to accept, modify, or reject. The credential carries the responsibility.

### Clinical Oversight

AI tools that influence RT clinical decisions should involve RT evaluation, pilot testing, and ongoing outcome monitoring.

### Documentation Standards

AI-assisted documentation must meet the same clinical and legal standards as human-authored notes. The RT who signs owns the content.

## WHAT THIS MEANS FOR YOU

### Be in the evaluation room

When your institution evaluates clinical AI, an RT should be in that room as a clinical evaluator — not just in the training session afterward.

### Apply the same lens you use for CPGs

What is the evidence? Who validated it? What population? What are the failure modes? The AARC has been teaching you this process for your entire career.

### Your skepticism is professional judgment

Asking hard questions about AI tools is not resistance to progress. It is exactly what your credential was designed for.

# Three Things Worth Watching (For Real)

## 01

### AMBIENT DOCUMENTATION

HIGH CONFIDENCE

Already deployed at scale. Real outcomes data. Measurable time savings. If your institution hasn't piloted this, the question is when, not if. Watch for RT-specific ambient documentation in the next 18–24 months.

## 02

### REVENUE CYCLE AI

HIGH CONFIDENCE

The insurance/billing layer is being disrupted hard. Denial prediction, prior auth automation, coding accuracy. Your institution's revenue cycle team is either using AI or evaluating it. This affects RT throughput and authorization workflows directly.

## 03

### PREDICTIVE DETERIORATION

VALIDATE IN YOUR POPULATION

Promising and actively evolving. Respiratory deterioration prediction is directly relevant to RT practice. Don't adopt blindly — demand validation data from your patient population. Be in the governance conversation.

# Thank You.

## Questions & Discussion

Keep these in your back pocket: **Which layer does this touch?** **What happens when it's wrong?** **Who owns the outcome?**

### David Eitel

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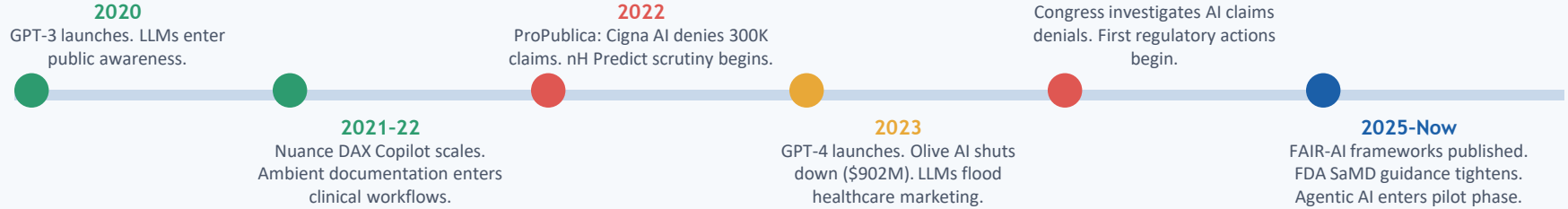
Adjunct Faculty · Utah Valley University

### Healthcare Uncharted

[HealthcareUncharted.com](https://HealthcareUncharted.com)

Critical analysis of healthcare AI — for clinicians, by clinicians. Slide deck available for download.

# AI in Healthcare: 2020 to Now



**THE PATTERN:** Operational AI (documentation, billing, scheduling) reached productive deployment first. Clinical AI is still navigating regulatory, validation, and liability frameworks. The gap between hype and deployment is widest in clinical decision support.

**WHY NOW IS DIFFERENT:** Scale of compute and training data has made AI qualitatively more capable than prior waves. But capability is not the same as safety, validation, or readiness for clinical use. That gap is exactly where your judgment matters.

# What “AI” Actually Means: A Plain-Language Taxonomy

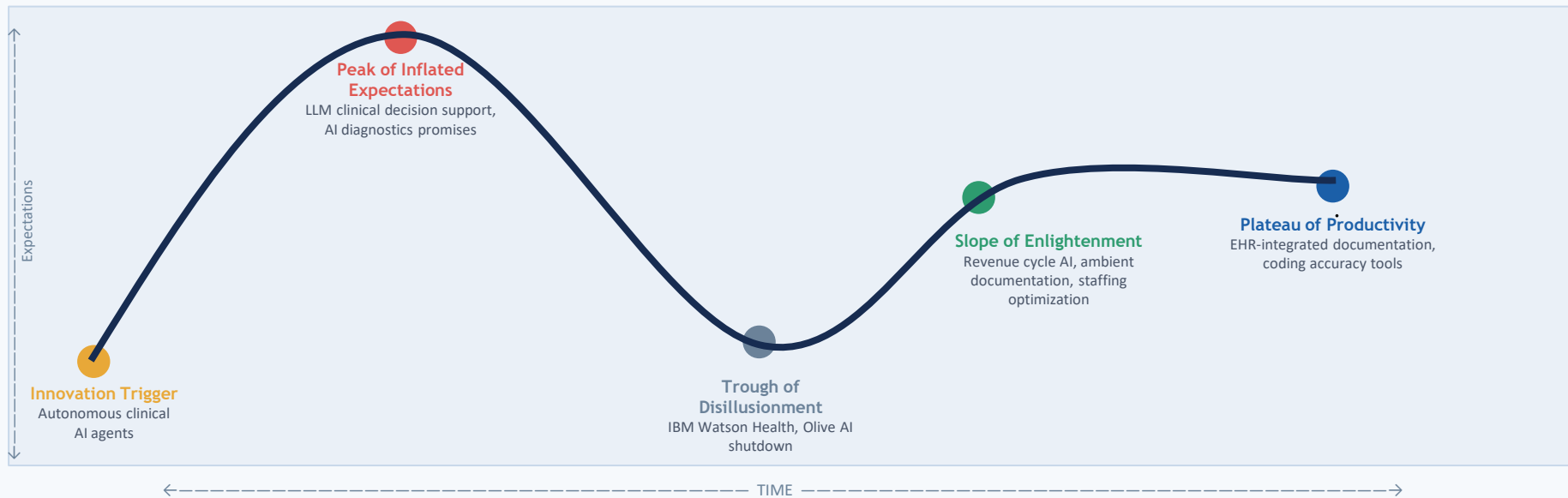
TYPE	WHAT IT ACTUALLY DOES	HEALTHCARE EXAMPLE	KEY LIMIT
<b>Rule-Based Systems</b>	Follows explicit IF-THEN logic written by humans. No learning.	Insurance coverage criteria, prior auth decision trees.	<i>Breaks outside its defined rules. Brittle to edge cases.</i>
<b>Machine Learning</b>	Finds patterns in data. Learns from examples without explicit programming.	Sepsis prediction scores, staffing demand forecasting.	<i>Performance depends on training data. Bias in = bias out.</i>
<b>Deep Learning</b>	Layered neural networks that recognize complex patterns in images and signals.	Radiology image reading, EEG/ECG analysis, vent waveform interpretation.	<i>Opaque decisions. Requires large labeled datasets and expert validation.</i>
<b>Large Language Models</b>	Predicts the most likely next word. Trained on vast text. Produces fluent language.	Ambient documentation, clinical note drafting, prior auth letter generation.	<i>Hallucination: produces confident, fluent, and sometimes false output.</i>
<b>Generative AI</b>	Creates new content (text, images, code) from learned patterns. Includes LLMs.	Denial letter generation, synthetic training data, patient communication drafts.	<i>Cannot distinguish what it generates from established fact. Requires human review.</i>
<b>KEY INSIGHT:</b>	Most “AI” in healthcare operations today is closer to sophisticated rule-based or ML systems than to GPT. That distinction changes how you evaluate the risk.		

# Generative AI, RAG, and Agentic AI: What's the Difference?

	INPUT TYPE	PRIMARY STRENGTH	KEY LIMITATION	BEST USE CASE
<b>Generative AI</b> <i>e.g. ChatGPT, Claude</i>	User text prompt	Creative content and synthesis. Strong at drafting, summarizing, and translating complex information.	Limited by training data. Hallucination: confident but sometimes false output.	Drafting clinical notes, summarizing literature, patient communication
<b>RAG</b> <i>Retrieval-Augmented Generation</i>	Query to specific documents directly	Factual answers grounded in real source documents — with citations.	Only as good as the documents it retrieves from.	Clinical policy Q&A, guideline lookup, evidence retrieval
<b>Agentic AI</b> <i>Autonomous multi-step AI</i>	High-level goal or objective	Autonomous multi-step task completion — no human prompting at each step.	Complex; higher error potential. Oversight design is critical.	Complex workflow automation — early stage in healthcare. Watch closely.

**TO LEARN MORE ABOUT RAG:** [aws.amazon.com/what-is/retrieval-augmented-generation](https://aws.amazon.com/what-is/retrieval-augmented-generation) · [ibm.com/topics/retrieval-augmented-generation](https://ibm.com/topics/retrieval-augmented-generation) · [NEJM AI: nejm.org/ai](https://nejm.org/ai)

# Healthcare AI: The Hype Cycle



**HOW TO USE THIS:** When evaluating any AI tool, ask: where on this curve does this technology actually sit? Vendors position everything near the Plateau. The three questions help you find out where it really is.

# Which AI Belongs at Which Layer?

HEALTHCARE LAYER	APPROPRIATE AI TYPE	REAL EXAMPLES	THE MISMATCH RISK
<b>Billing / Prior Auth</b>	Rule-based + ML. Pattern matching on codes, criteria, history.	Cigna, Waystar, Cohere Health.	Using LLM output for coverage decisions without human review.
<b>Operations / Documentation</b>	LLM for documentation capture; ML for scheduling and staffing.	Nuance DAX, Abridge; workforce management platforms.	Signing AI-generated notes without independent clinical review.
<b>Patient Monitoring / Alerting</b>	ML deterioration scoring on EHR, vitals, labs. Requires outcome feedback loop.	Epic Deterioration Index, Johns Hopkins TREWS.	High alert volume with no workflow design = alert fatigue, ignored warnings.
<b>Clinical Decision Support (RT Scope)</b>	Validated ML/Deep Learning only. IRB, FDA SaMD pathway, population-specific validation required.	SmartCare/PS (vent weaning), Hamilton automated protocols.	Deploying unvalidated tools using operational AI timelines and language.

# Glossary: Terms You Will Hear in Every AI Meeting

## Algorithm

A set of rules or instructions a computer follows to solve a problem. All AI tools contain algorithms.

## Model

The result of training an AI on data. The model is what makes predictions when deployed in your system.

## Training Data

The historical data used to teach the AI. Bias or gaps in training data produce bias or gaps in the model.

## Validation

Testing whether the model performs as expected in a real-world population. Ask: validated where, and on whom?

## Hallucination

When an LLM produces confident, fluent, and factually incorrect output. Not a bug — a known feature of how LLMs work.

## LLM (Large Language Model)

AI trained on massive text datasets to generate language. GPT, Claude, Gemini are LLMs. Produces fluent text; does not “know” facts.

## SaMD (Software as a Medical Device)

FDA classification for software that analyzes patient data to inform clinical decisions. Requires regulatory review.

## Ambient AI

AI that listens passively to clinical encounters and generates structured notes. Operates in the background, not at the point of decision.

## Alert Fatigue

When clinicians become desensitized to alerts due to high volume or low accuracy. A well-documented failure mode of AI alerting systems.

## Generative AI

AI that creates new content: text, images, or code. Includes LLMs. Cannot verify the accuracy of what it generates.