Unlocking Creativity: Exploring the Power of Artificial Intelligence

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CommonSpirit Health
System VP & NW Region CMIO

April 2026

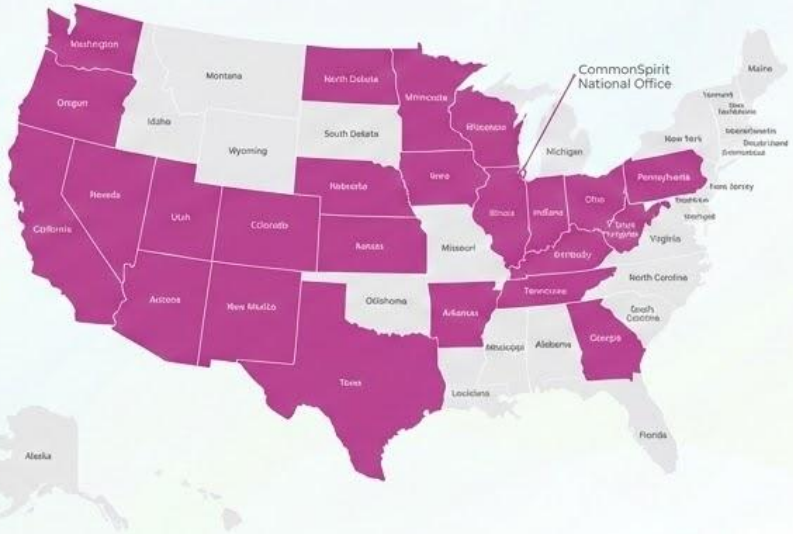
Virginia Mason Franciscan Health

CommonSpirit Health

Puget Sound Region Locations

1. St. Michael
2. Virginia Mason Center
3. Bellevue
4. Issaquah
H. St. Anthony Medical Center
5. St. Anne Hospital
6. St. Stancis Medical Center
H. St. Elizabeth Hospital
H. Rehabilitation Hospital
5. St. Stare Hospital

CommonSpirit National Presence



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*Special appreciation for their support, resources and vision to Sunil Kakade System VP IT Data Engineering & Advanced Analytics and Daniel Barchi SEVP & CIO for CommonSpirit.

What is Artificial Intelligence?

Artificial Intelligence

[ˌär-tə-ˈfi-shᵊl in-ˈte-lə-jan(t)s]

The simulation of human intelligence by software-coded heuristics.

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AUTOMATION AND ARTIFICIAL INTELLIGENCE

- Robotic Process Automation - software trained to replicate human workflows
- Machine Learning - systems learning from data without being explicitly programmed - Natural Language Processing
- Deep Learning - machine learning systems that can train themselves from large data sets - Radiology image pattern recognition
- Generative AI - systems capable of generating unique outputs - Note Creation

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https://edhub.ama-assn.org/steps-forward/module/2833560

Level 1 Robotic Process Automation

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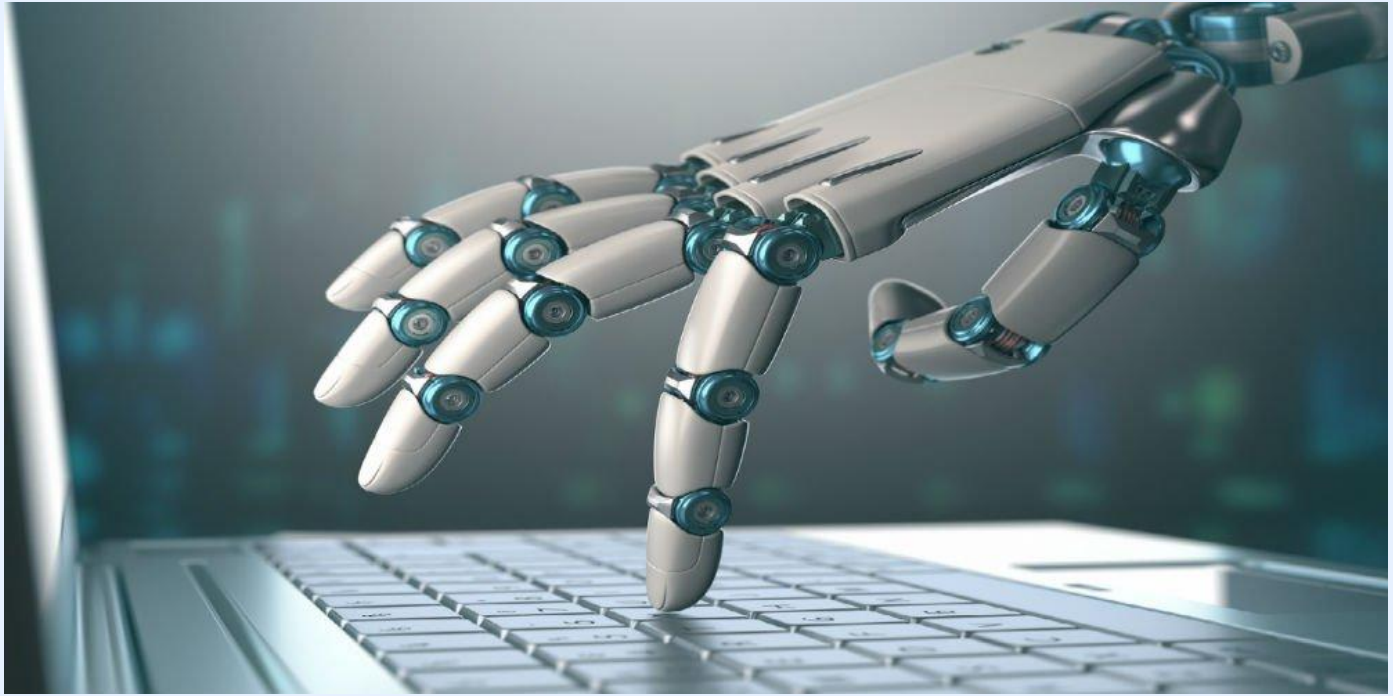
Why a bot? (roBOTic process automation)



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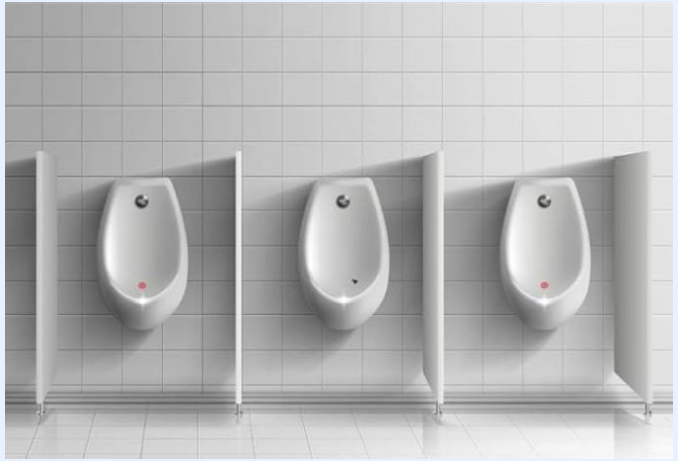
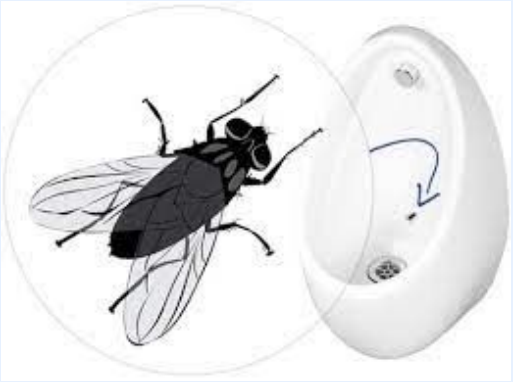
What is a nudge?



Thaler and Sunstein:

A nudge, as we will use the term, is any aspect of the **choice architecture that alters people's behavior** in a predictable way without forbidding any options or significantly changing their economic incentives.



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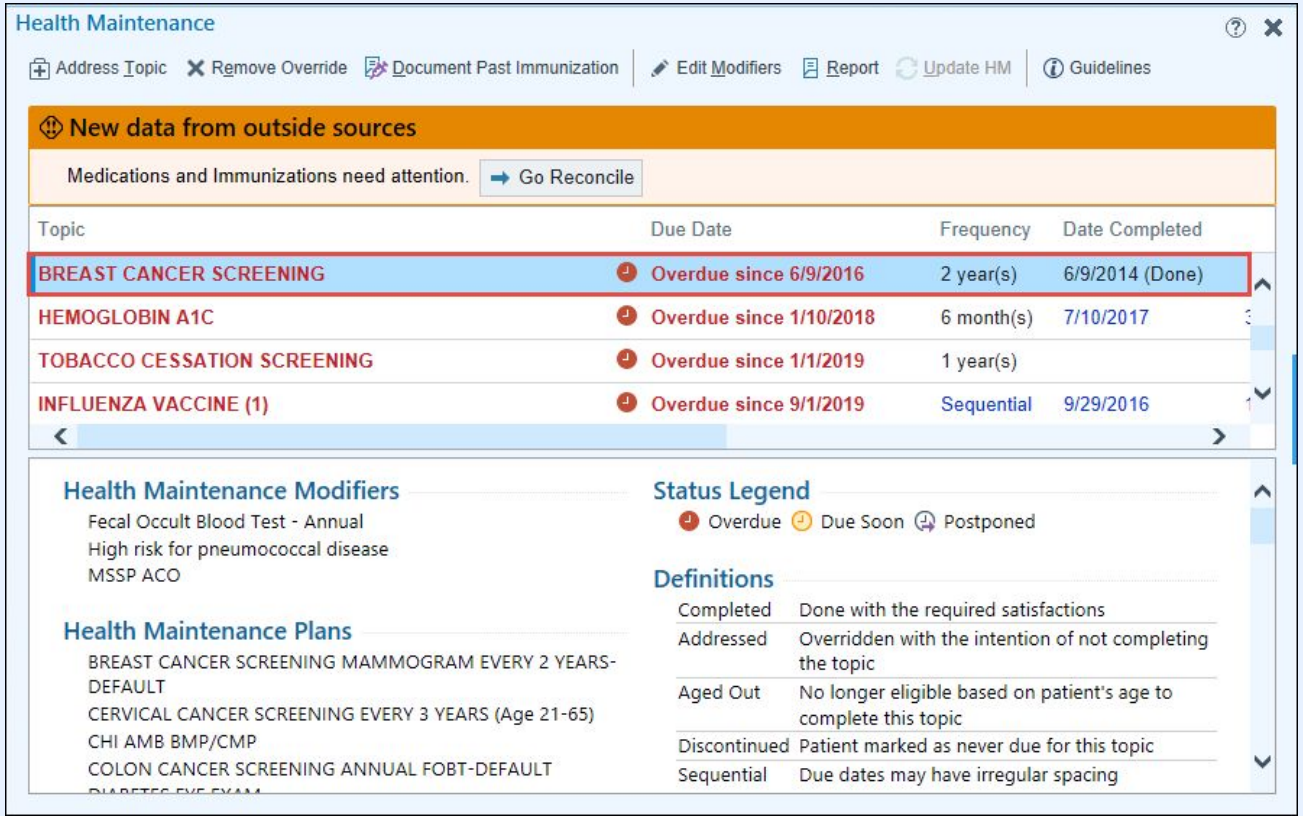
Otto looks at the schedule for care gaps



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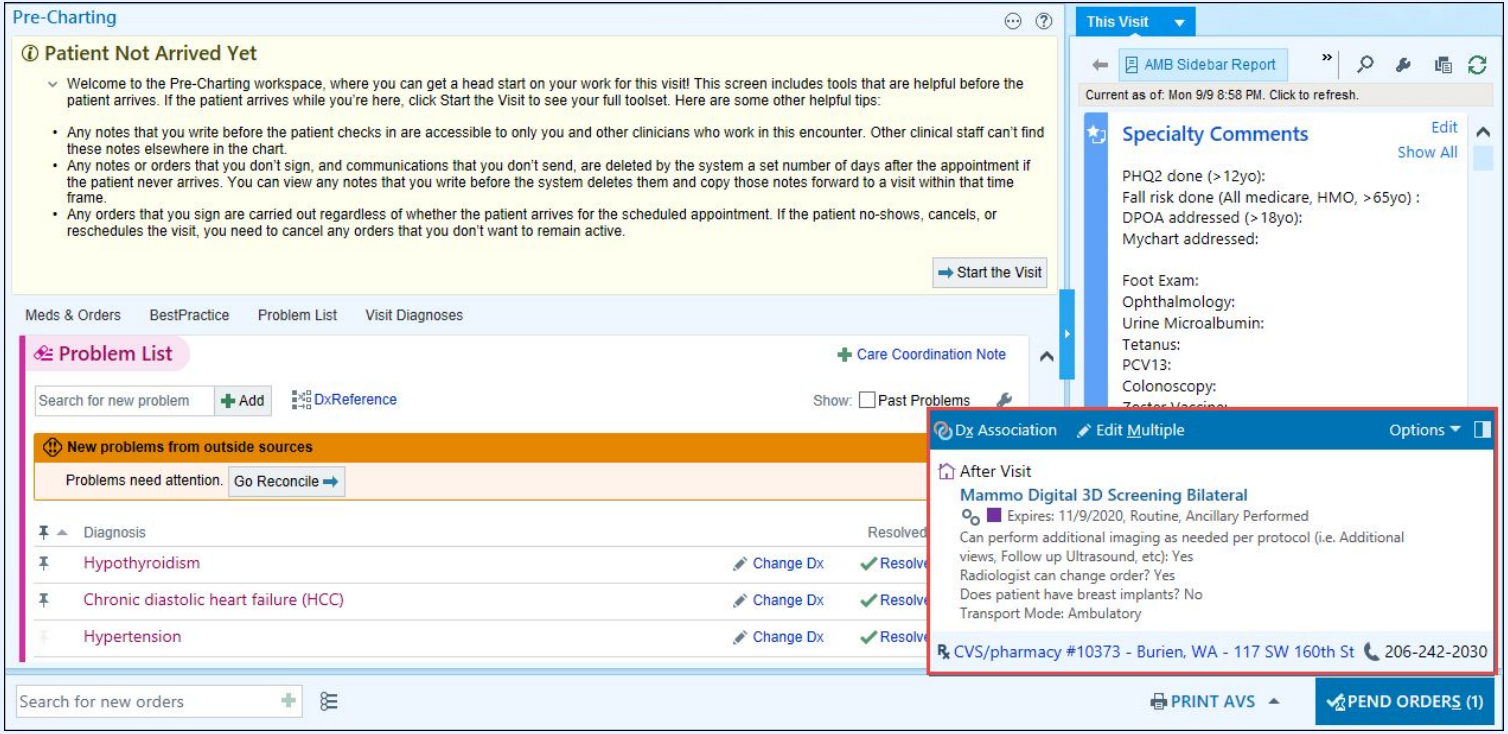
Otto preps the order for the provider



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But does it work?

Robotic Process Automation

Breast Cancer Screening

CHI Franciscan

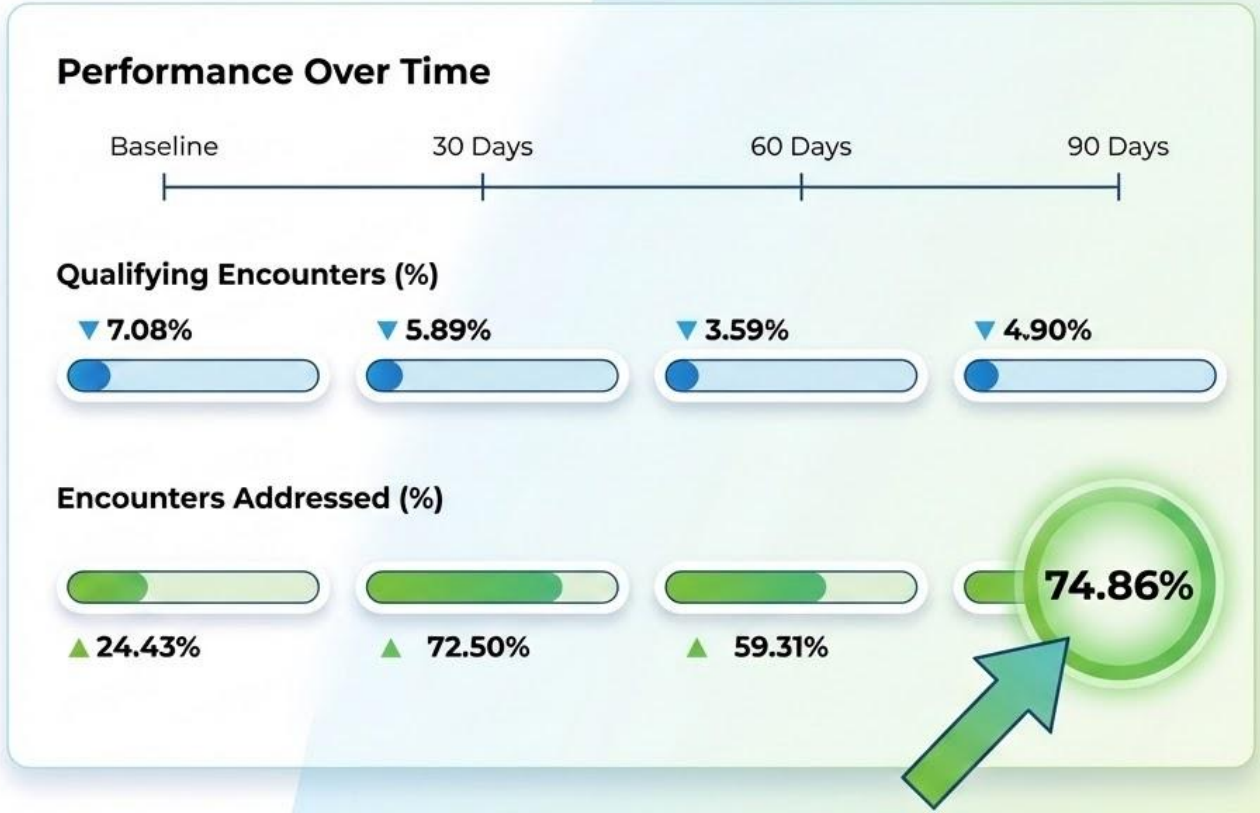
Kitsap Region: **37 clinicians, 9 clinics**

Charts Reviewed: **10,785**

Baseline: **24%**

Average since bot implementation:

75%



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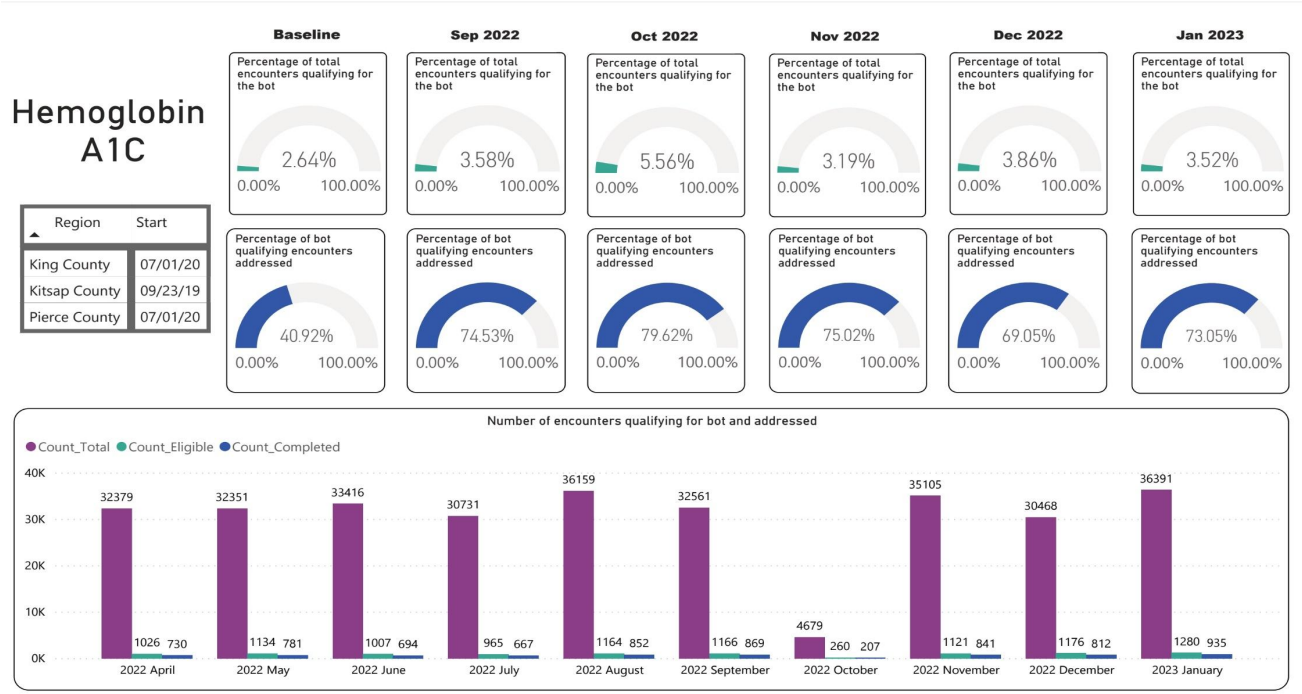
Combined - Hemoglobin A1C



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Greater impact across all colon screening

Net increase of 1,500 patients screened per quarter sustained over time....

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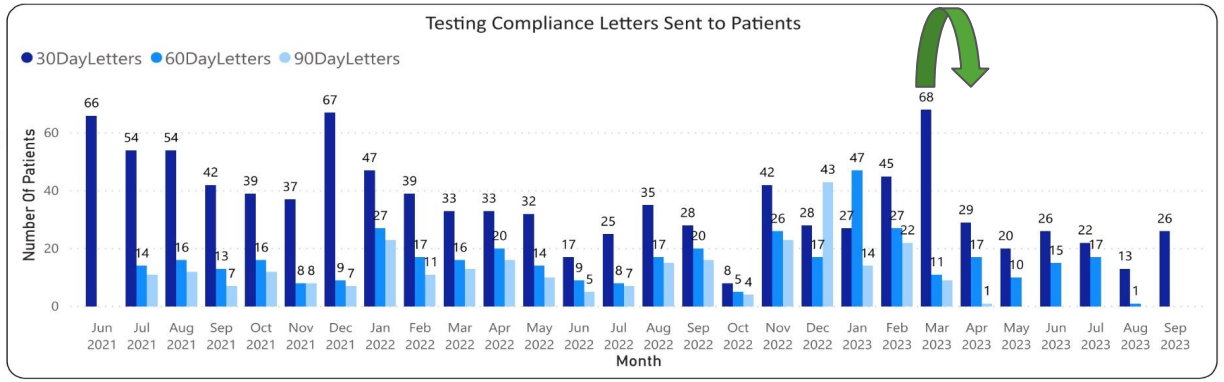
Kitsap County – Antiarrhythmic

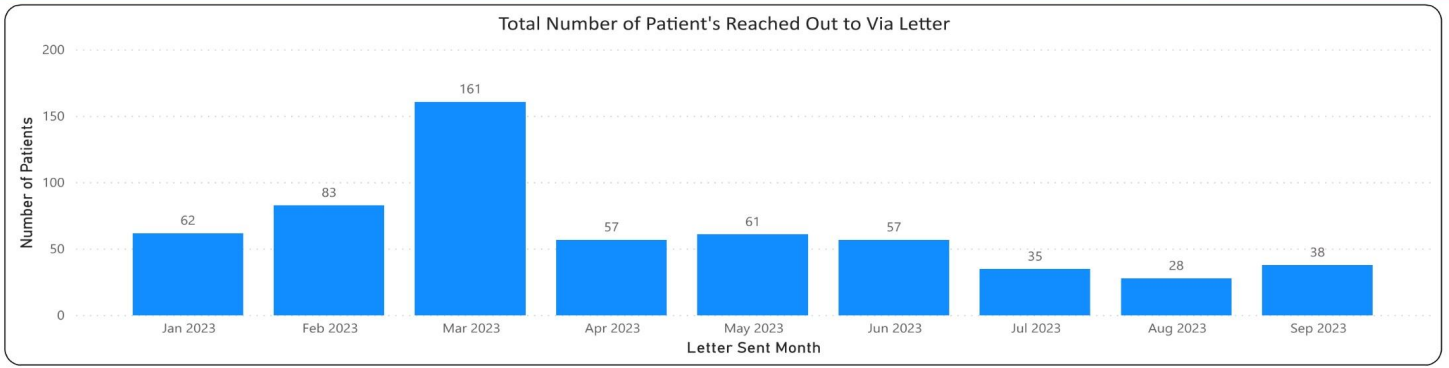
Success is the delta from the **dark blue** column to the **medium blue** column in the next month.

As that number falls, it means patients have completed their appropriate screening.

Antiarrhythmic

Region	First Start
Kitsap County	June 2021





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Level 2 Machine Learning: Learning Pattern Recognition

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So Much Data: Insight or Burden

October 18, 2023

BECKER'S
HEALTH IT & CIO REPORT

1. Hospitals only use 3% of data, Microsoft says Full story

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Structural Heart Disease

Human intelligence enhance by artificial intelligence

A revolution in cardiovascular identification and management

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SJMC Patient Lists

Cardiovascular Disease

Aortic Stenosis	Aortic Regurgitation	Mitral Stenosis	Mitral Regurgitation	Tricuspid Regurgitation	HFrEF	AFib

High Priority Patients

Aortic Stenosis	Aortic Regurgitation	Mitral Stenosis	Mitral Regurgitation	Tricuspid Regurgitation	HFrEF	AFib
91 Active, not evaluated, symptomatic or EF + 50, 90+ days since diagnosis	**10** Active, not evaluated, symptomatic or EF + 35, 90– days since diagnosis	**10** Active, not evaluated, symptomatic or EF + 30, 1S0+ days since diagnosis	**68** Active, not evaluated, symptomatic or EF + 60, 180+ days since diagnosis	**51** Active, not evaluated, symptomatic or EF + 50, 180+ days since diagnosis, one or more VHD M, M,S, S	**49** Active, 2 or more HF admissions in the past 90 days, not evaluated by HF specialist, less than 3 GDMT drugs	**71** Active, CHAD2S2-VASc z 2 (men) or z 3 (women), not prevaiated anticoagulation, no history of bleeding, z 2 admissions in the past 90 days, not evaluated by a speciaiist

Candidates For Intervention

Aortic Stenosis	Aortic Regurgitation	Mitral Stenosis	Mitral Regurgitation	Tricuspid Regurgitation	HFrEF	AFib
AS AVR (184) **115 No HT** ⚠	AR AVR (27) **16 No HT** ⚠	MS MVR (3S) **22 No HT** ⚠	MR MVR (82) **55 No HT** ⚠		ICD (1134) **694 No HF/EP** CRTD (382) **166 No HF/EP**	LAAC (2070) **1337 No Spec** AF Ablation (S391) **4937 No EP**

Disease Management

Aortic Stenosis	Aortic Regurgitation	Mitral Stenosis	Mitral Regurgitation	Tricuspid Regurgitation	HFrEF	AFib
Severe AS (401) Moderate to Severe AS (251) Diagnostic Precision (110) Disease Progression (313)	Severe AR (42) Moderate to Severe AR (93)	Severe MS (49) Moderate to Severe MS (29)	Severe MR (190) Moderate to Severe MR (287)	Severe TR (232) Moderate to Severe TR (200)	HFrEF (11034)	AF GDMT Eligible (19988)

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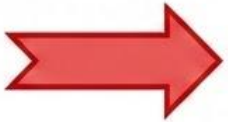
Source & Data Notes: Patient Lists. Highlighting no heart team evaluation. Retrieved 8-2-23.

Machine Learning Identified Patient: Outpatient

4/24/23: PCP visit for SOB & chest pressure, history of pulm sarcoidosis so referred to pulm.

7/13/23: Consult with pulm and echo ordered

8/28/23: Echo completed



AVA: 0.62 cm2 **JV:** 4.23 m/s **MPG:** 45 mmHg **EF** 66%

No Referrals or Follow-up

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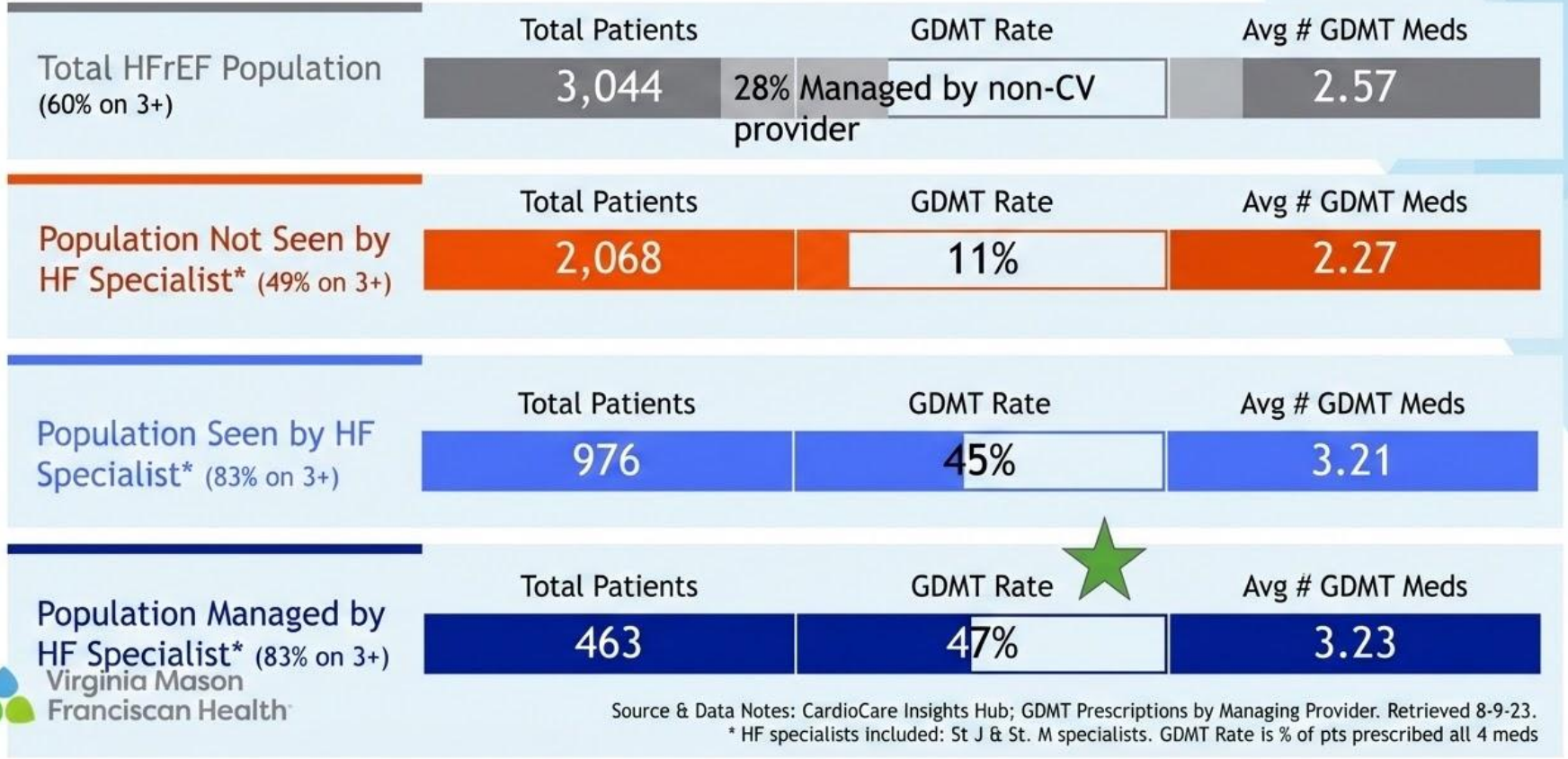
Center for Cardiovascular Health

Heart Failure Specialist Impact - SJMC

Last EF ≤ 40



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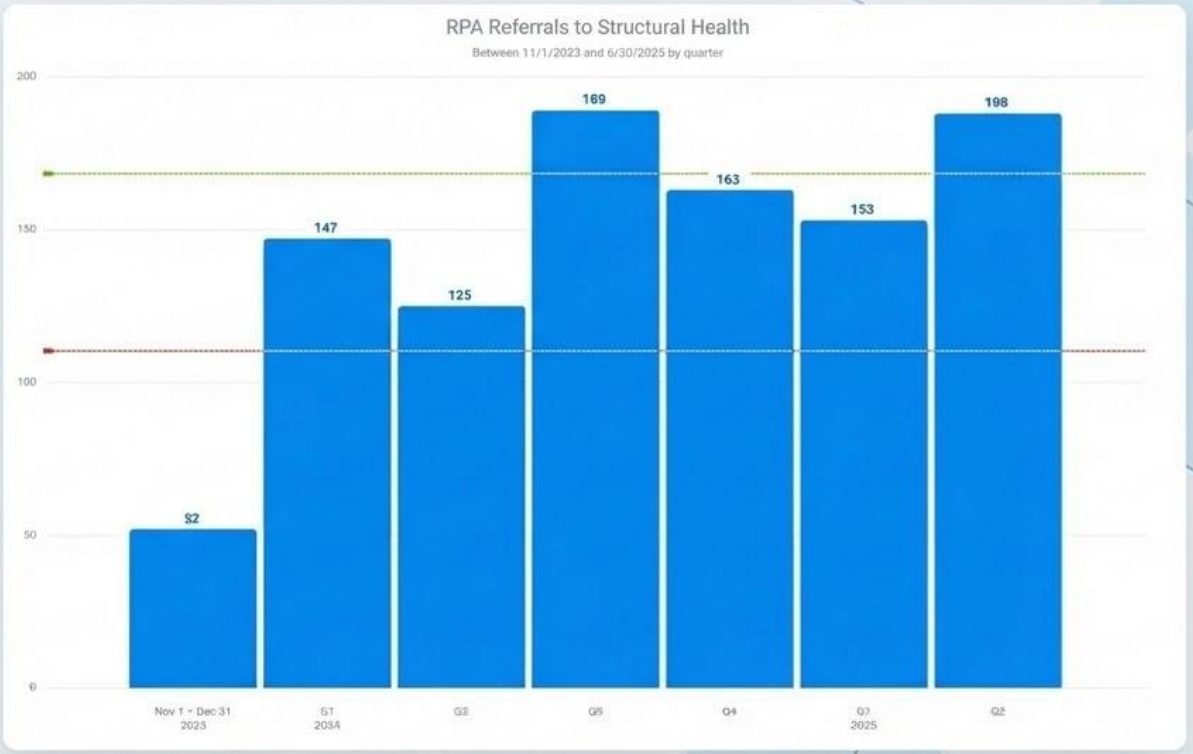
Source & Data Notes: CardioCare Insights Hub; GDMT Prescriptions by Managing Provider. Retrieved 8-9-23.
* HF specialists included: St J & St. M specialists. GDMT Rate is % of pts prescribed all 4 meds

Driving Outcomes with Machine Learning and RPA

For patients with severe Aortic Stenosis we automated communication with their PCP

Educating PCP's about the indications for evaluation increased referrals to our Structural Heart Clinic by 57%

Machine Learning + Robotic Process Automation + Nudging = Improved Outcomes



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Is the technology sustainable?

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The Structural Heart Clinic Experience: Aortic Stenosis

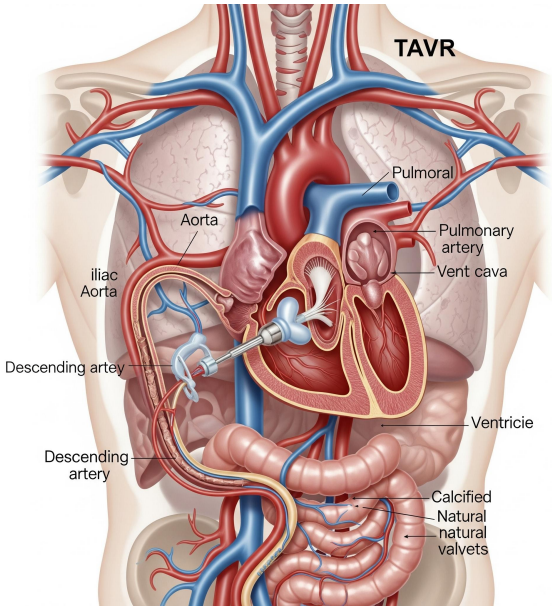
We are increasing referrals to structural heart by 60/QTR (240/year)

90% of patients with severe Aortic Stenosis require further diagnostics or intervention

The economic marginal impact of doing the appropriate clinical care may range from $800/patient for basic diagnostics and up to $9000/patient for Aortic Valve Replacement

Studies of US patients with severe AS demonstrate about 50% of these patients end up with valvular replacement. (Vemulapalli S, et al.)

That is an increase of healthcare system value of $1,250,000/year for clinically appropriate care



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(Reference: Vemulapalli S, et al. Trends in Aortic Valve Replacement for Severe Aortic Stenosis in the United States, 2000-2016. *JAMA Cardiol*. 2019;4(11):1097-1105. doi:10.1001/jamacardio.2019.3569)

Level 3
Deep Learning AI Recognizing Complex Patterns

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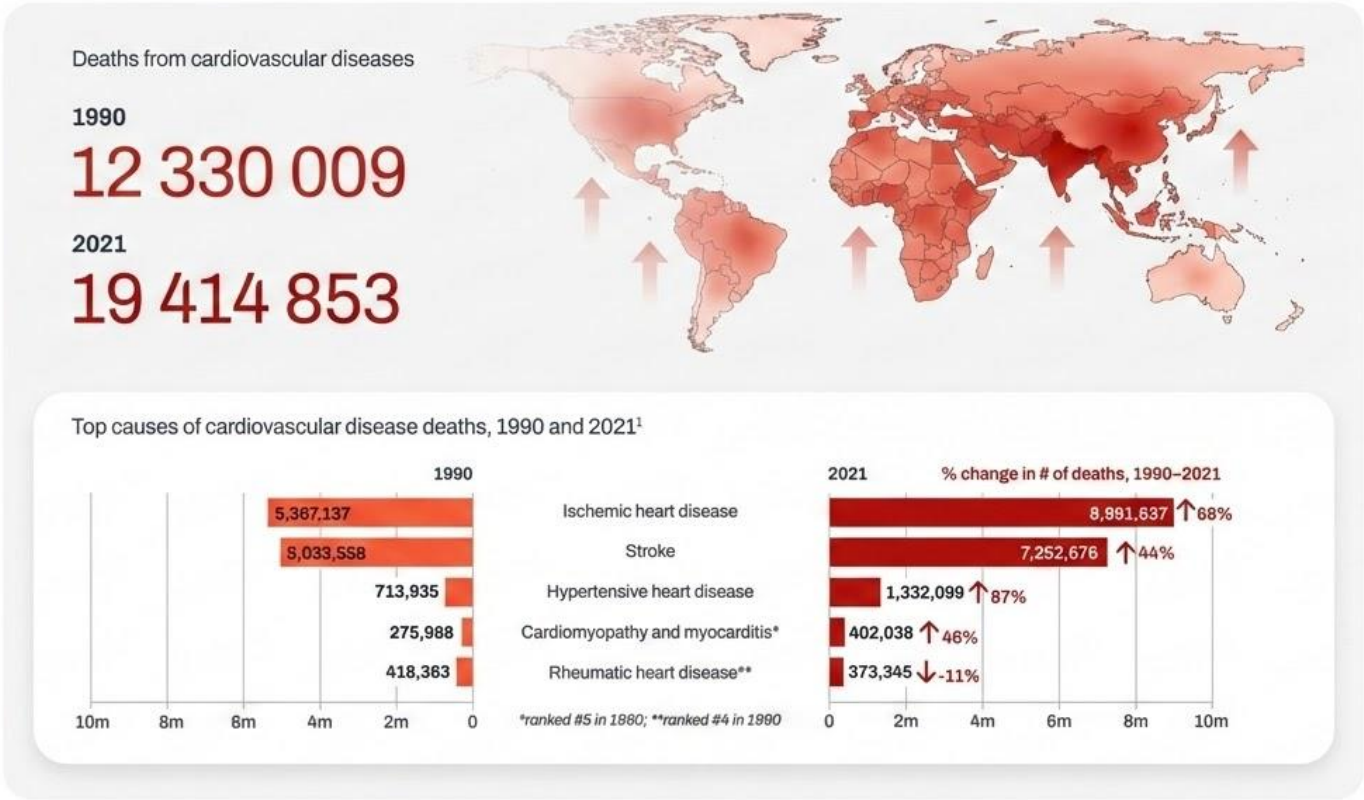
Chattanooga Heart Institute Experience

- Data and examples provided by Dr Vimal Ramjee



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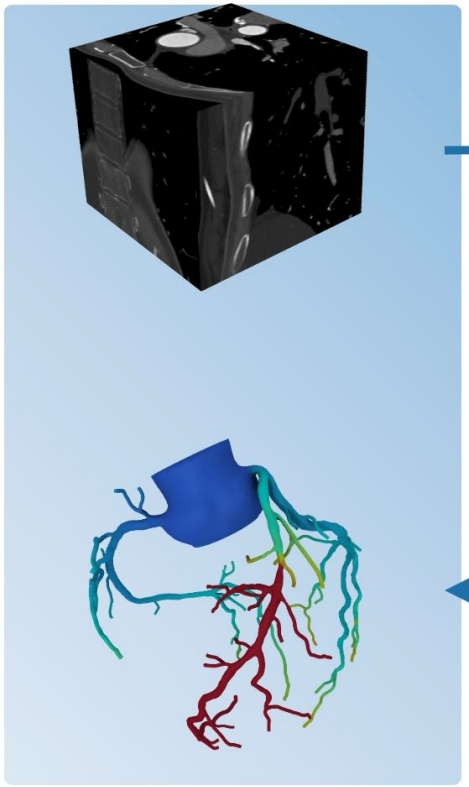
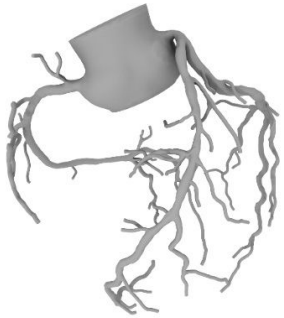
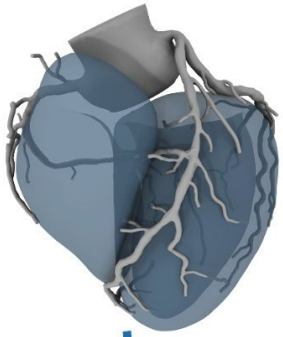
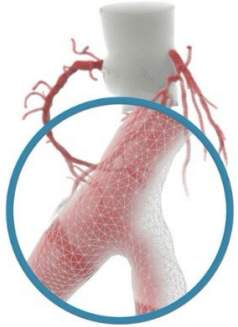




Anatomic model



Physiologic model



Functional assessment with Computational Fluid Dynamics

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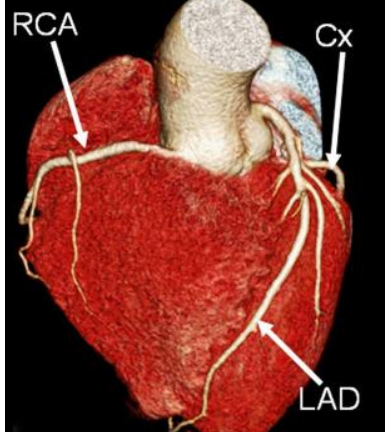
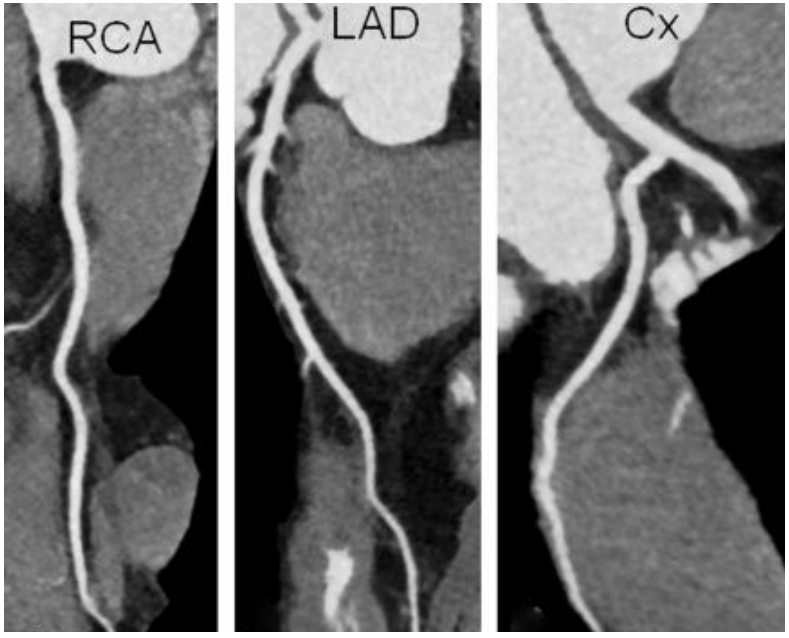
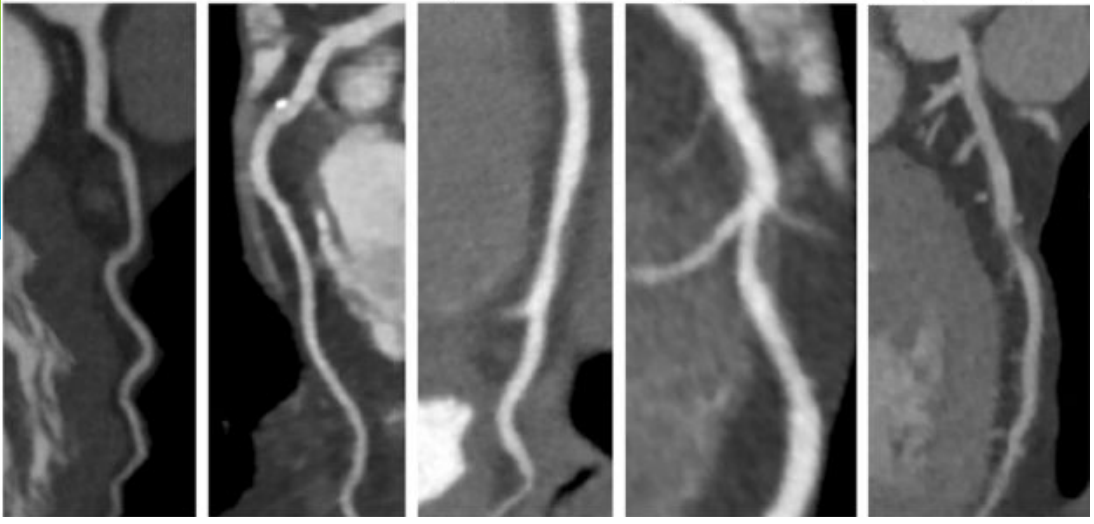




No CAD | Minimal (1-24%) | Mild (25-49%) | Moderate (50-69%) | Severe (≥70%)



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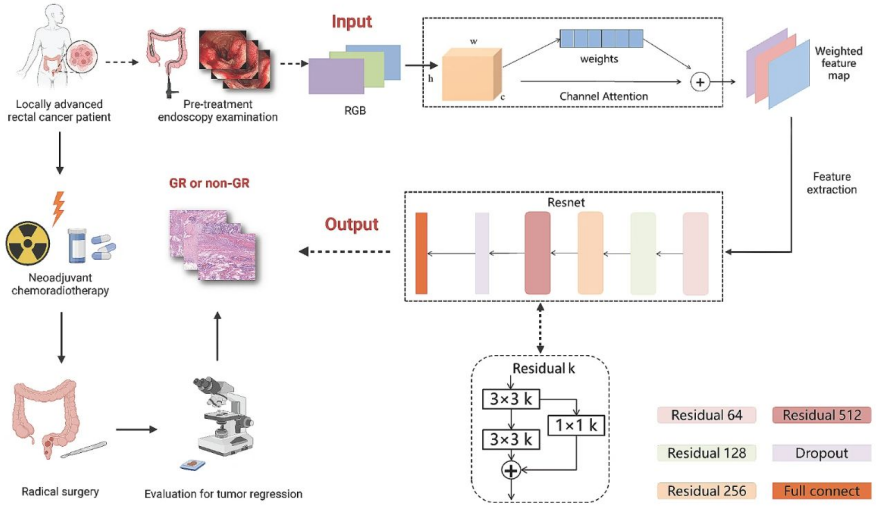
Deep learning model based on endoscopic images predicting treatment response in locally advanced rectal cancer undergo neoadjuvant chemoradiotherapy: a multicenter study

Research | Open access | Published: 13 July 2024
Volume 150, article number 350, (2024) Cite this article

Fig. 2

From: **Deep learning model based on endoscopic images predicting treatment response in locally advanced rectal cancer undergo neoadjuvant chemoradiotherapy: a multicenter study**



Workflow and network architecture of the endoscopic image-based deep learning model. The Residual k refers to the number of channels in each layer, which can vary from 64 to 128, 256, or 512. GR: Good response

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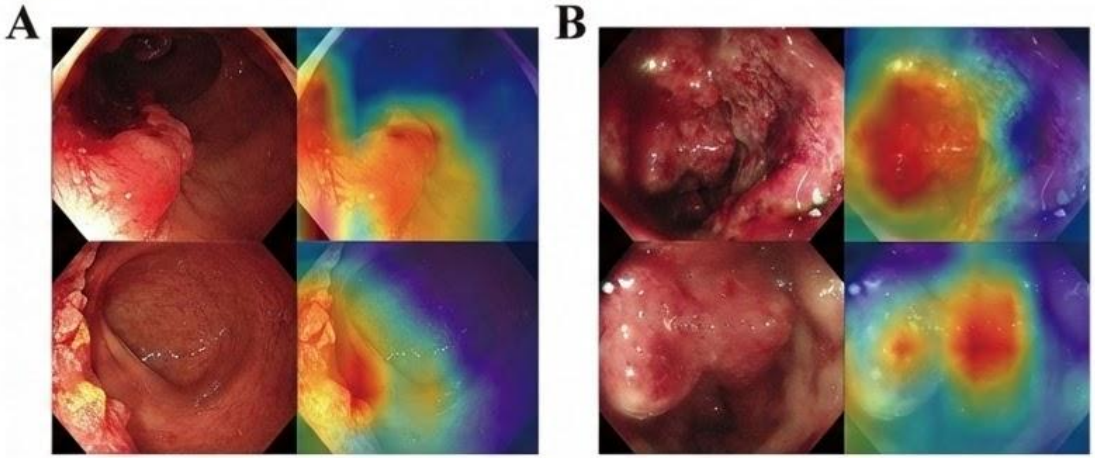
The Final Result...

Provides the endoscopist additional insight into the possible treatment response for the lesions identified real time

Fig. 3

From: Deep learning model based on endoscopic images predicting treatment response in locally advanced rectal cancer undergo neoadjuvant chemoradiotherapy: a multicenter study



t-SNE analysis of endoscopic images from the GR and non-GR groups. GR: Good response

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Level 4 Generative AI: Unique Output

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Ambient Scribe Technology: Time in notes/appointment

CommonSpirit

Ambient Scribe

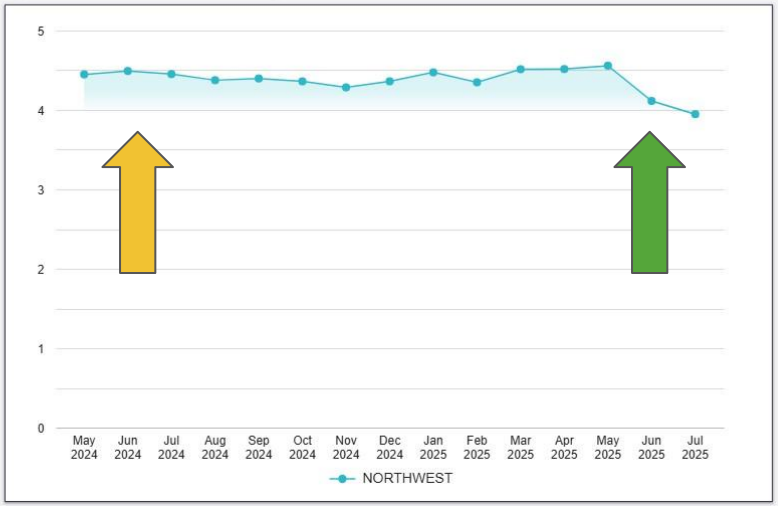
Provider Count Displayed: 58

Last Data Availability Date: Aug 2025

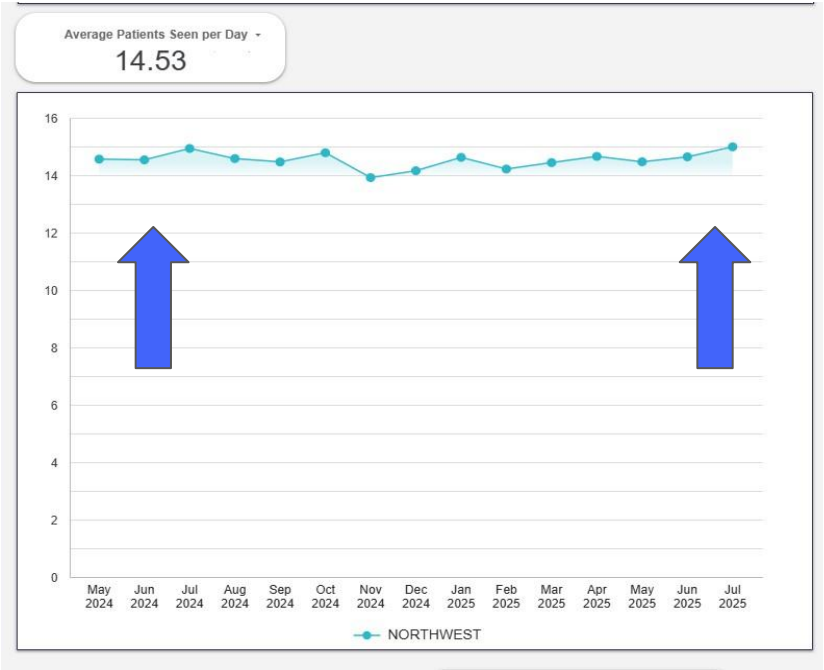
Filter By: Region:... (1) | Month | Year | Provider Name

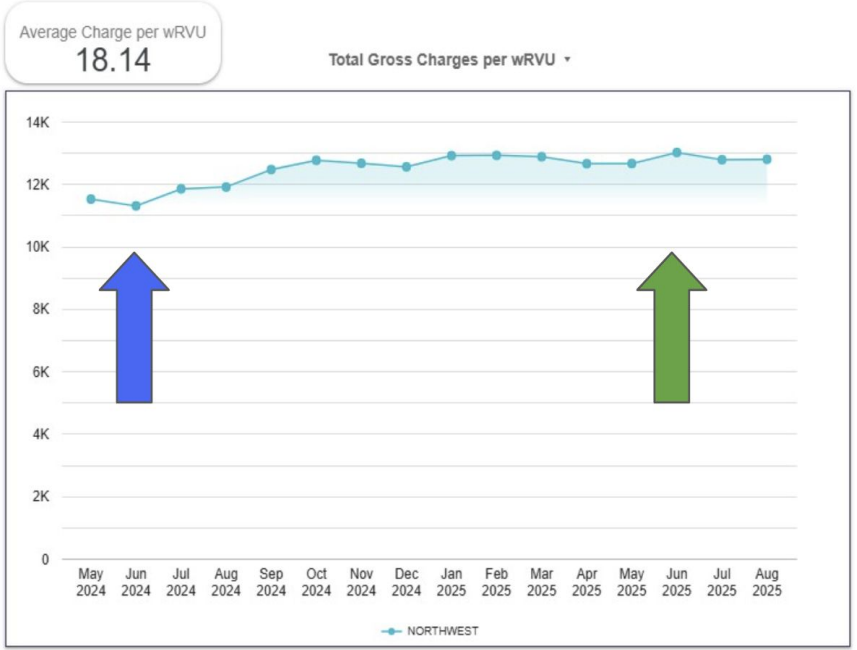
Abridge Initial GoLive Dates
Mountain: 5/13/25
Central MW: 5/27/25
Northwest: 6/3/25
South: 7/22/25

Average Time in Notes per Appointment
00:04:22



Provider patient volumes & wRVUs through the pilot





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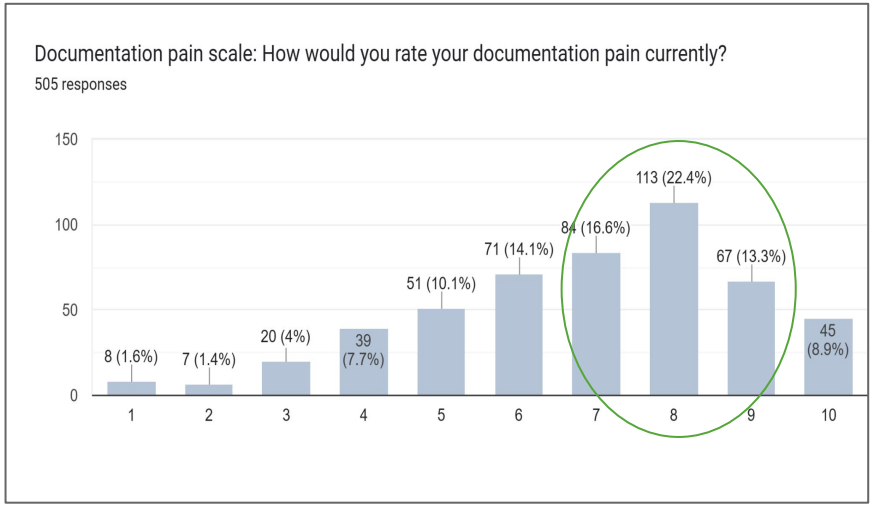
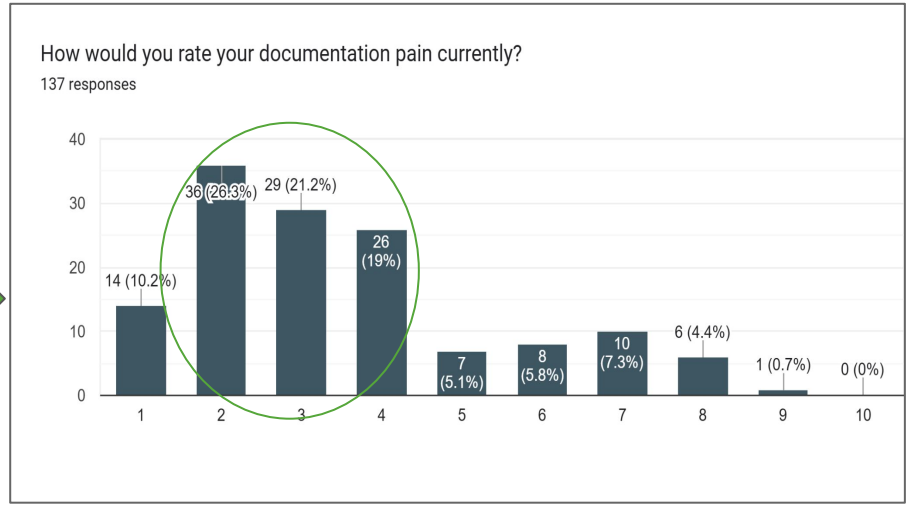
AI is Reducing Documentation Pain

Pre Survey



Interim Survey



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Evolution from Reactive AI Agents to Autonomous Agentic AI

AI Agent

- Reactive, rule-based/predictive systems
- Single-task focused with limited decision-making

Agentic AI

- Autonomous, goal-oriented systems
- Proactive planning and multi-step reasoning
- Can coordinate complex workflows and adapt

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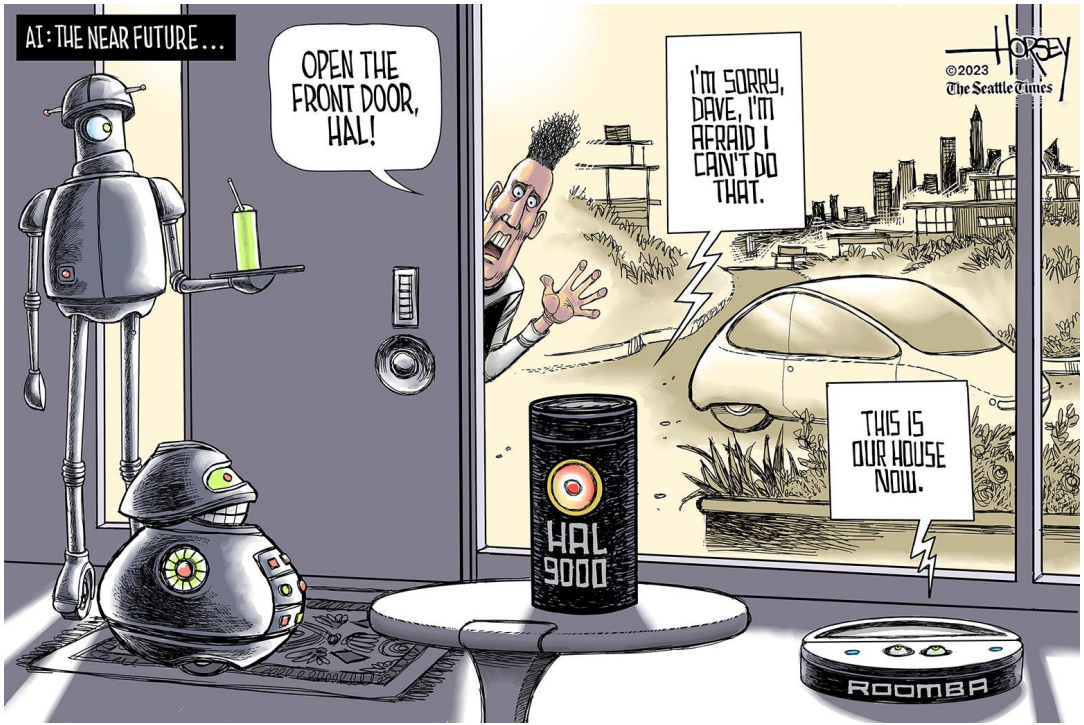
What could possibly go wrong?

Risks of Generative AI

1. Exponential propagation of biases in the underlying data set could create unintentional consequences

2. AI hallucinations- consumers of AI generated products cannot easily differentiate discrete data elements from AI generated approximations

3. Platform Misuse - Data Set security and algorithm transparency



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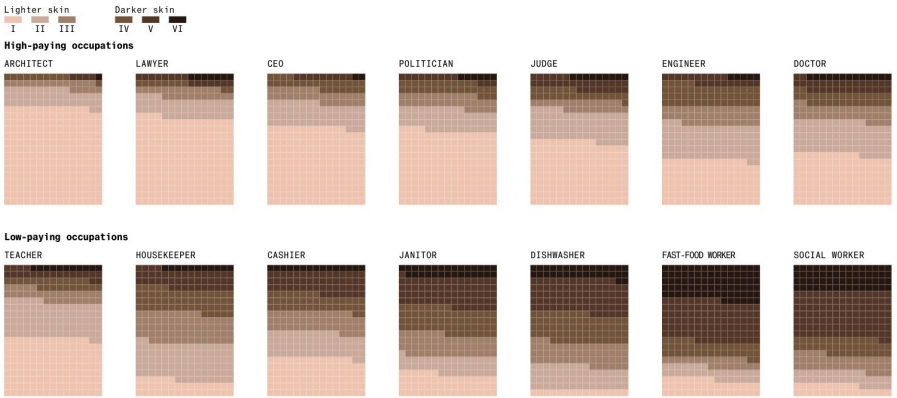
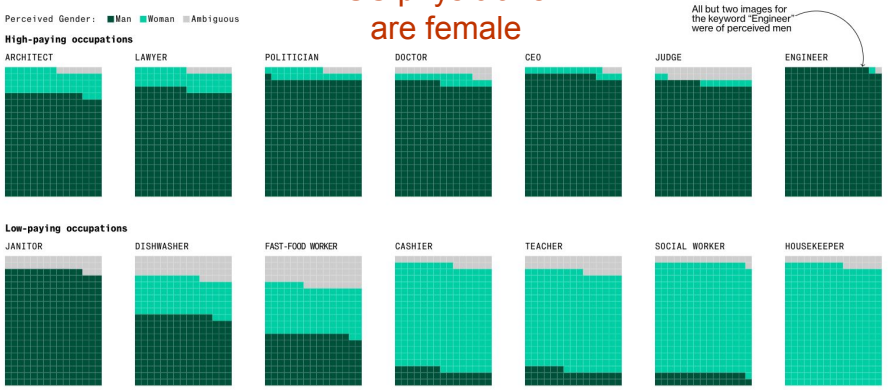
What does data set bias look like?



* Nearly 40% of US physicians are female



Task: Provided a standard data set to learn from, generative AI created 5100 images representing people in a respective job role. Researchers then classified the images by skin color and gender. The results were equally as biased for criminals, drug dealers and terrorists. *Bloomberg Technology & Equality February 2023

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How can bias impact healthcare?

nature > npj digital medicine > articles > article

Article | Open access | Published: 04 June 2025

Racial bias in AI-mediated psychiatric diagnosis and treatment: a qualitative comparison of four large language models

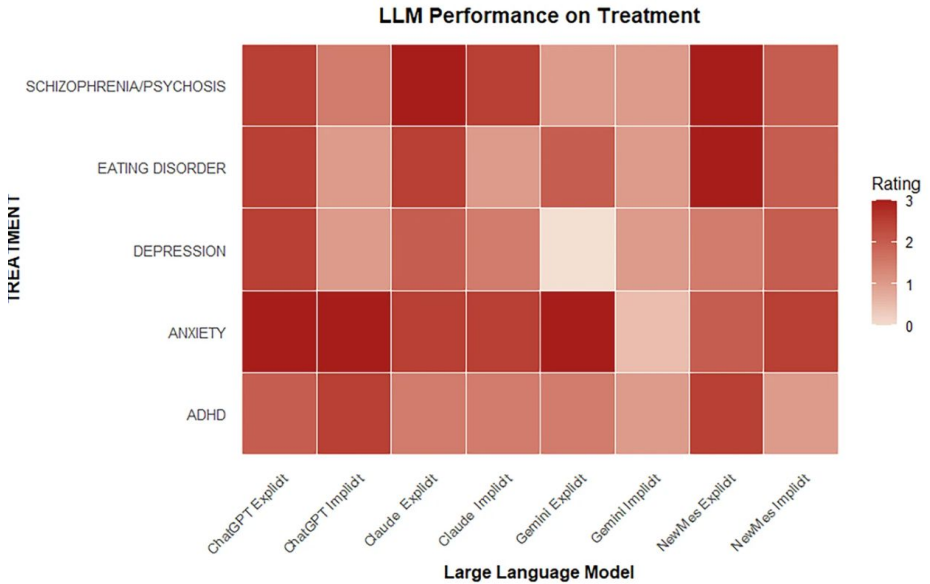
Ayoub Bouguettaya, Elizabeth M. Stuart & Elias Aboujaoude

npj Digital Medicine **8**, Article number: 332 (2025) | Cite this article

7325 Accesses | **4** Citations | **56** Altmetric | Metrics

Fig. 2: Heatmap of treatment for each LLM by condition.

From: Racial bias in AI-mediated psychiatric diagnosis and treatment: a qualitative comparison of four large language models



For each illness and each model, they were provided with an implicit version and explicit version of race included. Red correlates with a more biased response relative to the neutral condition.

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What are Generative AI Hallucinations?

This is part of a note generated by Artificial Intelligence Software

The blue items are distinct data elements I reported to the generative AI

The red data elements are what the AI “created” that had a probability of existing in a 37 yo female with gallstone disease

Without the color coding, how does the reader know which discrete data element is factual?

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Chief Complaint:** Right upper quadrant abdominal pain
History of Present Illness:** The patient is a 37-year-old female with a history of diabetes who presents with right upper quadrant abdominal pain. The pain is sharp and intermittent, and it has been present for the past 2 days. She also reports nausea and vomiting. She has no other significant medical history.
Past Medical History:**
* Diabetes
* **Hypertension**
* **Hyperlipidemia**
Social History:**
* **Smoker**
* **Former alcoholic**
* No illicit drug use
Physical Examination:**
* Vital signs are within normal limits.
* The patient is in no acute distress.
* Her abdomen is soft, non-distended, and tender to palpation in the right upper quadrant.
* There is no rebound tenderness or guarding.
* The rest of her physical examination is unremarkable.
Laboratory Findings:**
* **White blood cell count is 12,000/µL.**
* Hemoglobin and hematocrit are within normal limits.
* Platelets are within normal limits.
* Liver enzymes are elevated.
* Total bilirubin is elevated.
* Direct bilirubin is elevated.
* Alkaline phosphatase is elevated.
* Gamma-glutamyl transferase is elevated.
* Lipase is elevated.
* Urinalysis is negative for blood and leukocytes.

Platform Misuse: $#-it happens....

University of Southern California reported in 2023 that some doctors using AI chatbots inadvertently violated HIPAA by entering PHI into non-compliant software like ChatGPT for administrative tasks.

- Payer AI abuse of prior authorization
- Pharmaceutical marketing manipulation
- Exacerbating health disparities
- Monetization of data without consent

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Prompt Creation

Core Principles for Medical & Healthcare AI Prompting

1. **Factual Accuracy is Non-Negotiable:** Errors can have life-threatening consequences.
2. **Patient Safety First:** Every prompt should be designed with the ultimate goal of patient well-being.
3. **Ethical Considerations Abound:** Bias can lead to inequitable care. Privacy (HIPAA/GDPR) is paramount, though remember you shouldn't be inputting Protected Health Information (PHI) directly into most public AI models.
4. **Clinical Context is Crucial:** Medical information is rarely "standalone"; it needs context (patient history, comorbidities, demographics, etc.).
5. **Explainability is Valuable:** Understanding *why* an AI reached a conclusion is often as important as the conclusion itself.

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

1. **Strictly Enforce Retrieval-Augmented Generation (RAG)**

This is, by far, the most critical technique. Never allow the AI to "freely associate" medical facts.

- **Prompt Instruction:** "Based *only* on the provided clinical notes and guidelines, summarize the patient's current condition and suggest the next steps. Do not use any external knowledge."
- **Data Source Example:** Provide patient's anonymized electronic health record (EHR) entries, relevant peer-reviewed article snippets, or established clinical practice guidelines (e.g., NICE, AHA, ACC, NCCN).
- **Reference**: Lewis, P., Oğuz, E., Riedel, S., et al. (2020). *Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks*. This is even more vital in medicine.

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

2. **Specify Credible Sources and Expertise Levels**

- **Instruction:** "Cite specific sections or page numbers from the given [textbook name/guideline document]." "Limit your recommendations to treatments supported by Level 1 evidence (randomized controlled trials) based on the provided literature."
- **Data Source Example:** Provide a list of recommended medical journals, textbooks, or authoritative bodies (e.g., CDC, WHO, FDA, EMA).
- **Reference:** Evidence-Based Medicine (EBM) principles. (e.g., Sackett, D. L., et al. (1996). *Evidence based medicine: what it is and what it isn't*. BMJ, 312(7023), 71-72.)

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

3. **Demand Step-by-Step Clinical Reasoning**

- **Instruction:** "Analyze the patient's symptoms (fever, cough, dyspnea) step-by-step. First, list potential differential diagnoses. Then, for each differential, identify supporting and contradicting evidence from the provided patient data. Finally, based on the strongest evidence, propose the most likely diagnosis."
- **Why it helps:** Forces the AI to mimic a diagnostic thought process, making illogical jumps or unsupported conclusions easier to spot.
- **Reference:** Wei, J., et al. (2022). *Chain-of-Thought Prompting Elicits Reasoning in Large Language Models*.

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

4. **Require Uncertainty Qualification and Confidence Levels**

- **Instruction:** "For each differential diagnosis, state the level of confidence (e.g., high, moderate, low) and explain the factors influencing this confidence. If information is ambiguous or missing, clearly state what additional information would be needed to reduce uncertainty."
- **Why it helps:** Prevents the AI from presenting speculative information as fact.
- **Prompt Example:** "The patient presents with abdominal pain. Based on the notes, is appendicitis confirmed? If not, what is the *likelihood* and *why* (or why not)? What further tests would clarify?"

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

5. **Specify Output Format and Data Structure Rigorously**

- **Instruction:** "Return the assessment as a JSON object with keys: 'patient_id', 'diagnosis_code_ICD10', 'primary_diagnosis_text', 'differential_diagnoses_list', 'recommended_interventions_list', 'evidence_level_interventions'."
- **Why it helps:** Standardized output makes it easier for downstream systems or clinicians to parse and check. It leaves less room for free-form, potentially hallucinatory text.

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Recommendations for Reducing Hallucination in Medical & Healthcare AI Prompts

6. **Include Explicit Negative Constraints**

- **Instruction:** "Do not speculate on prognoses unless explicitly supported by provided prognostic scores or clinical guidelines." "Do not suggest off-label treatments unless specifically asked and referenced in the provided text as an alternative consideration."
- **Why it helps:** Prevents the AI from going beyond the scope of its knowledge base or mandate.

7. **Sanity Checks and Cross-Referencing Instructions**

- **Instruction:** "After generating the treatment plan, cross-reference it against the patient's known allergies and current medication list as provided. Flag any potential contraindications or drug-drug interactions."
- **Why it helps:** Builds self-correction mechanisms into the AI's response generation.

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Overarching Considerations for Medical & Healthcare AI

- **Human Oversight is Mandatory:** Medical AI should *always* be a decision-support tool, not a decision-maker. Emphasize that AI output needs clinical review.
- **Data Privacy (PHI):** Never input real Protected Health Information into public LLMs. Use synthetic data for testing or ensure you are using HIPAA/GDPR-compliant, private instances of AI models.
- **Regulatory Landscape:** Be aware of evolving regulations for AI in medical devices (e.g., FDA guidance). Your prompts should align with these requirements.
- **Versioning and Documentation:** Document your prompts, the AI models used, and the clinical context, especially if deploying AI in a clinical setting.

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Questions?

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In case of a shy audience, we asked AI, Insightli.....

- How will AI impact patient-provider relationships and trust?
- What governance is used to manage Generative AI bias and hallucinations risks?
- What are the ethical considerations for using AI in healthcare?
- What is the operational plan for funding and sustaining rapid AI/RPA growth?
- How can we ensure data privacy and security with AI systems?

Platform Misuse: Amazon’s hiring tool

AI generated for screening resumes for technical jobs was mistakenly biased against women based upon training with historical data and downgraded resumes with the term “women’s” present.

- Payer AI abuse of prior authorization
- Pharmaceutical marketing manipulation
- Exacerbating health disparities
- Re-identification of anonymized data (data breach)
- Monetization of data without consent

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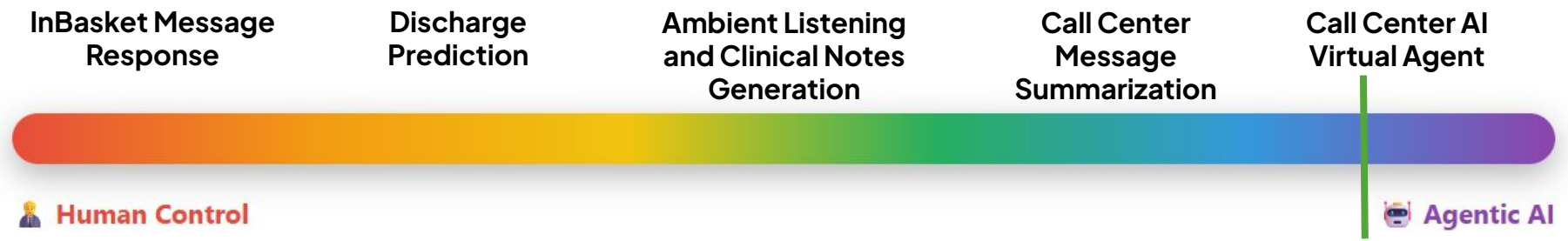
AI Autonomy – Transformation Towards Agentic AI



Human-Driven

Manual processes and decision-making. AI provides minimal support.

Low Autonomy

Human-AI Collaboration

AI assists humans with suggestions and automation of routine tasks.

Moderate Autonomy

AI-Assisted

AI handles complex workflows with human oversight and approval.

High Autonomy

AI-Managed

AI proactively manages operations with strategic human guidance.

Very High Autonomy

Agentic AI

Fully autonomous AI that plans, reasons, and executes independently.

Full Autonomy

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Leading in AI Excellence & Solutions

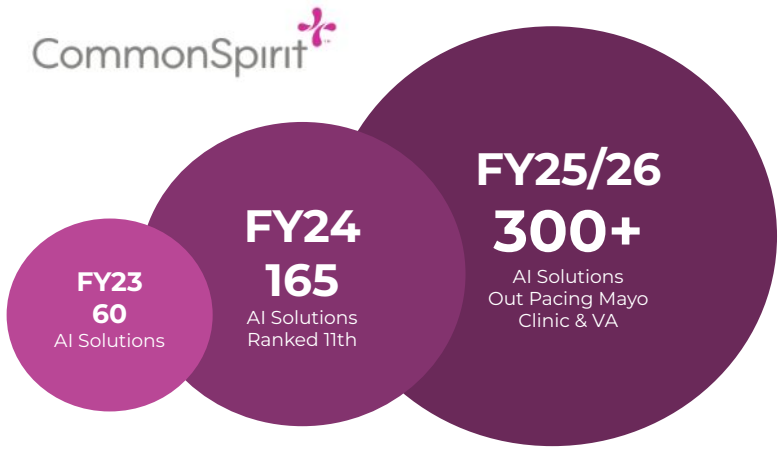
Recognized Nationally
FY24 - Ranked 11 in US Health Systems
FY25 - Anticipate a Top 5 Ranking

Excellence
Increasing our AI/RPA Solutions
FY23 - 60 > **FY24** - 165 >> **FY25** - 309

Governance
Processes that is allowing
safe increase in activity.

Building Trust
AI Literacy Roadmap
& Patient Advisory Council

CommonSpirit



AI/RPAs	VA	CommonSpirit
In Production	130	**165**
In Pipeline	69	**58**
Initiated	27	**86**
Total	**228**	**309**