

The Transformation of Health Systems by Generative AI

Frederick Chang, DO, MAS, MMM, FHM

Disclosures

- I have no direct relevant relationships to disclose.
- Please note: Some of the products here are utilized by Yuma Regional Medical Center. By naming the products, they are not a personally endorsement of the product by me nor do I have any direct financial relationships.

About Me

- Graduate of Western University of Health Sciences, COMP – 2013
- Chief Medical Information Officer, Yuma Regional Medical Center
 - Only health system in Yuma County, Arizona
 - 400+ acute care hospital, 24 bed psychiatric facility, 40+ ambulatory clinics, 300+ employed providers
 - Co chair of the Artificial Intelligence Subcommittee at YRMC
 - Epic Electronic Health Record
- Assistant Clinical Professor, University of Arizona, College of Medicine
 - Faculty - Bioinformatics Department
 - Alma Matter for CI Fellowship (Board Certification for Clinical Informatics, ABPM)
 - Teach 4 Clinical Informatics Fellows (2 fellows x 2 year fellowship)
 - Certification from American Board of Artificial Intelligence in Medicine

Objectives

The Transformation of Healthcare Systems by Generative AI

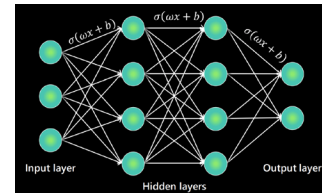
1. Identify how Large Language Models work
2. Identify safety principles when using Generative Artificial Intelligence (AI) tools
3. Identify groundbreaking use cases of Generative Artificial Intelligence in Healthcare Systems

What is Generative Artificial Intelligence?

How does Generative Artificial Intelligence work?

Generative Artificial Intelligence uses mathematical weights to determine the context.

An osteopathic doctor can perform ...



Word	Probability Weight
medicine.	0.04
OMT.	0.21
visit.	0.10
physical exam.	0.13

Source: <https://microsoft.github.io/Workshop-Interact-with-OpenAI-models/llms/>

How does Generative Artificial Intelligence work?

Mathematical weights are then assigned to sentences, then paragraphs to contextualize the text.

An osteopathic doctor can perform OMT. ➡

The osteopathic doctor needs to check for somatic dysfunction to do OMT.

The osteopathic doctor needs to hospitalize his/her patient to do OMT.

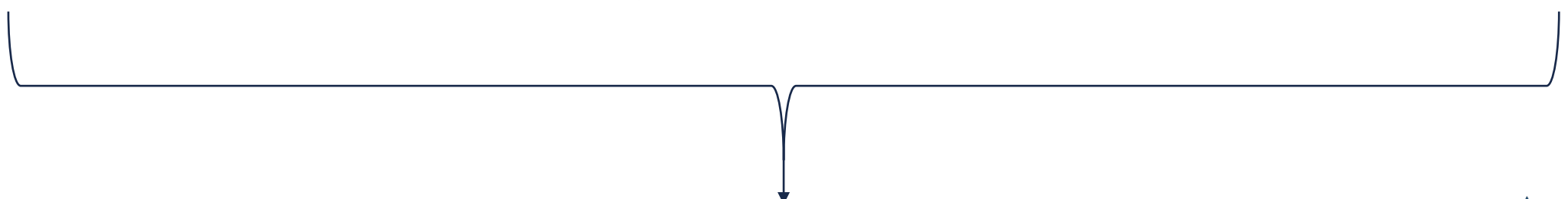
The osteopathic doctor needs to refer the patient to a surgeon.

The osteopathic doctor uses a robot to perform OMT.

What is the next sentence?

Big Names in Large Language Models

Large language models are trained based on a large amount of texts from textbooks and internet websites. They learn from how humans have documented their interactions in the world. These models then power Generative AI tools.



“Large Language Models”

Generative AI Safety

Safety Principles in Artificial Intelligence

- "Human in the Loop" principle
- Users are responsible for the outputs
- Be aware of Hallucinations (incorrect outputs)
- Protected Health Information (PHI) should not be placed in Generative AI tools in non-sanctioned environment (ie, ChatGPT should be used in Epic sandbox environment)



Image: ChatGPT4o

Ambient Dictation



Ambient Dictation

“Doctor, my back has been hurting for about 1 month.”

“I have tried acetaminophen.”



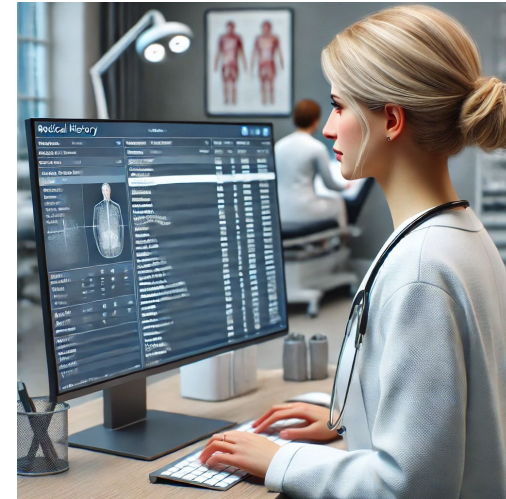
“What have you tried?”

“Have you tried OMT?”

Image: ChatGPT4o

Ambient Dictation

“A few seconds later”

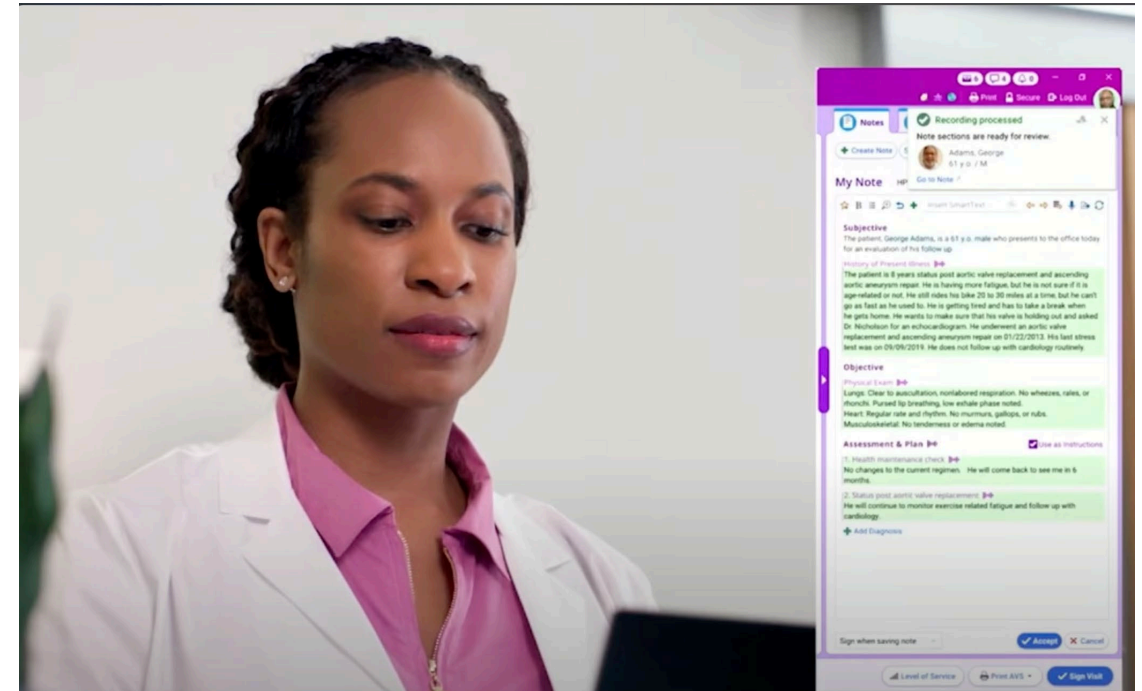


Note is completed as you walk out of the room

Image: ChatGPT4o

Pros of Ambient Dictation

- Improved Patient and Clinician relationship
- Improved Documentation Accuracy
- Reduce Pajama Time
- Reduce Note Writing Time
- Customizable to Specialty Workflow
 - Plug and Play with specialty LLM?



Source: Generative AI in Healthcare with Nuance and Epic at Microsoft Inspire 2023 <https://www.youtube.com/watch?v=R8YR243hbNA>

Cons of Ambient Dictation

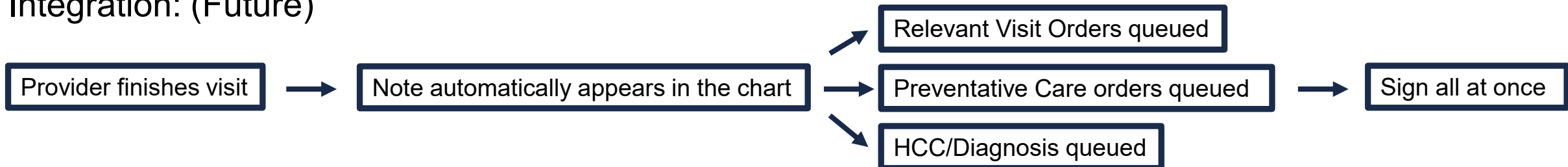
- Use mostly proven in outpatient settings
- Integration into Electronic Medical Record is variable (Workflow!)
- Cost can be very expensive; some organizations passing costs to providers

Current versus Future State of Ambient Dictation

No Integration:



Integration: (Future)



Billing/Coding



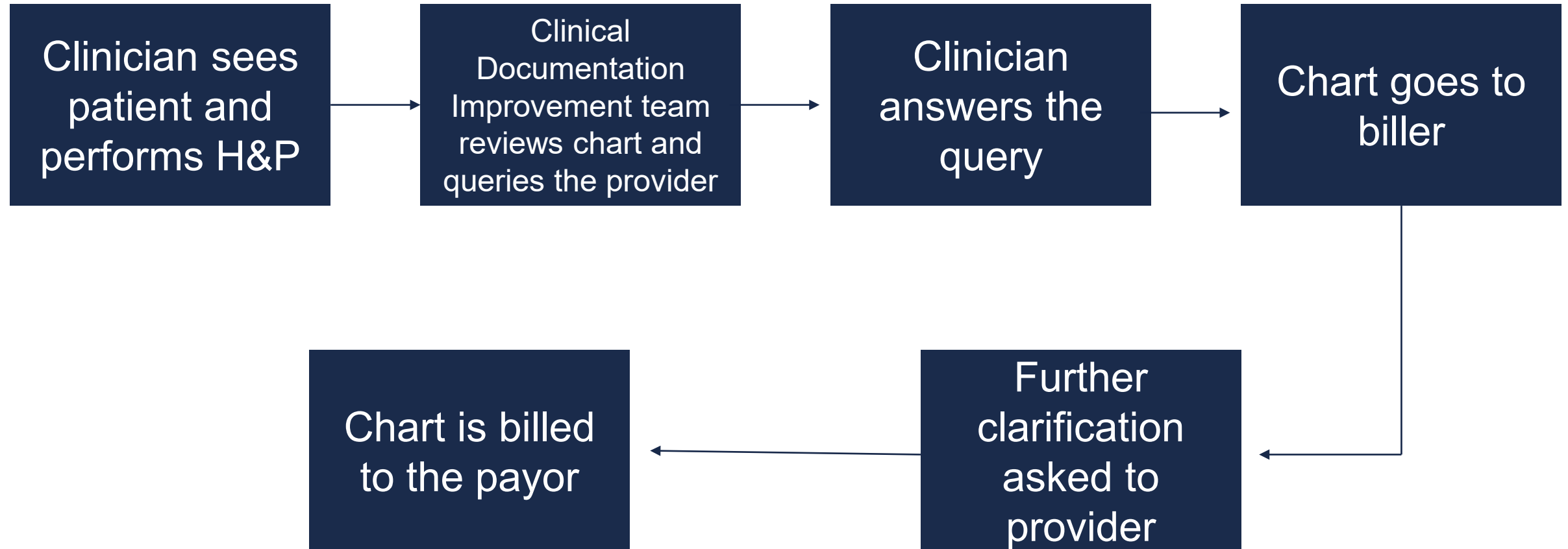
Billing/Coding

Health systems use teams of staff to perform Billing and Coding. There is benefit, especially for the inpatient side.

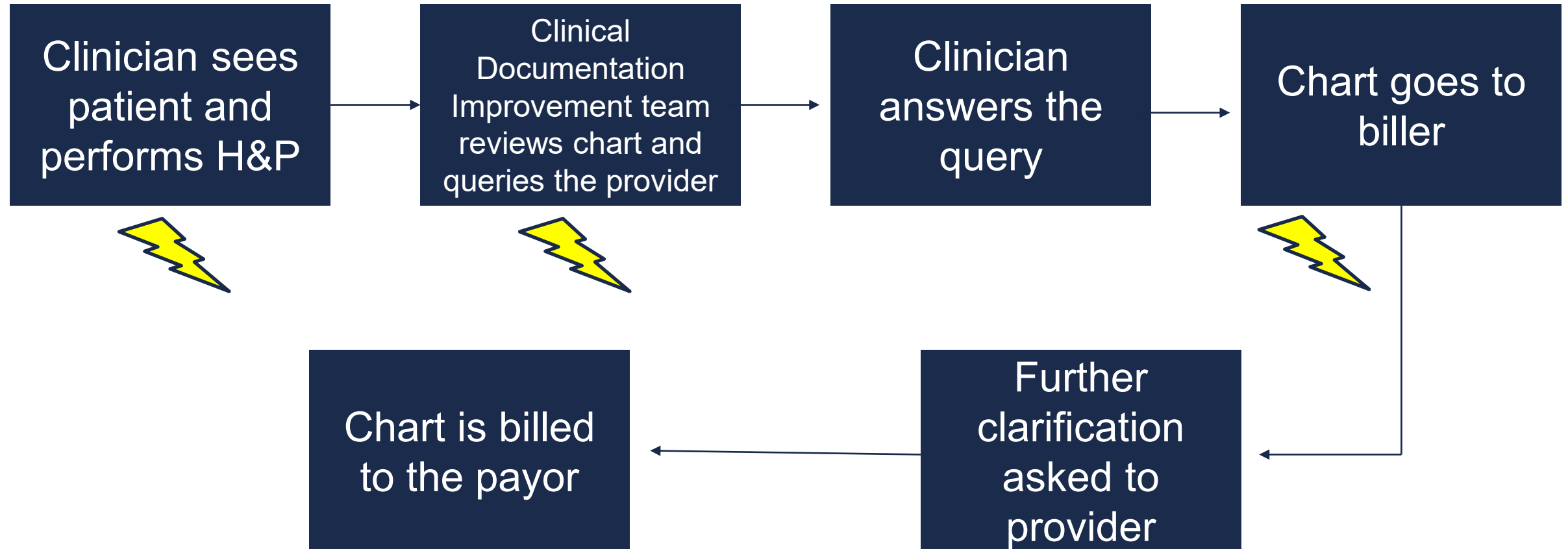
Goals of Generative AI:

- Help query more charts (Volume)
- Help query charts more efficiently (Workflow interception)
- Help identify high dollar amount charts (Efficiency)

Workflow for Clinical Documentation Improvement



Workflow for Clinical Documentation Improvement



- Identify Charts
- Generate Queries
- Analyze Missing Codes

Coding Benefits

- Improve Documentation Accuracy
- Improve Billing Cycle by expediting human workflows
- Allow CDI team to spend time more efficiently on high value charts

The screenshot displays a software interface for clinical documentation. On the left, there are two panels: 'Documented Diagnoses and Procedures' and 'Documentation Opportunities'. The top panel shows a list of diagnoses and procedures, including 'K80.00 | Calculus of gallbladder w acute cholecyst w/o ...' with a 'Working DX: DRG-446' tag. The bottom panel shows 'Diagnoses (2)' and 'Clinical Evidences (1)', with entries like 'N17.9 | Acute kidney failure, unspecified' and 'A41.9 | Sepsis, unspecified organism'. On the right, three document preview panels are shown. The top two are 'Operative Report (10/26/2023 - 03:15 PM) Provider: Bedford, Audrey, M.D. | General Surgery', with the text 'Gangrenous Gallbladder with stones' highlighted. The bottom panel is 'History & Physical (10/26/2023 - 08:05 AM) Provider: Williams, Jane, M.D. | Internal Medicine', with 'WBC 20.0 x 10e3 / mL' highlighted.

Source: Nuance: <https://www.nuance.com/healthcare/provider-solutions/clinical-documentation-improvement/cde-one.html>

Other Future Tools



Other Generative AI Tools

- Summarizing Chart Review (including HIE)
- Create discharge summaries for Hospitalists
- Advanced Chatbot to improve Patient Access via Patient Portal
- Automated Cancer Staging
- Translate Discharge Instructions/Visit Summaries to Patient's Preferred Language
- Ask questions regarding population health metrics or patient panel (creating graphs/stats)
- In-Basket Message Response



Original Investigation | Health Informatics

Large Language Model–Based Responses to Patients' In-Basket Messages

William R. Small, MD, MBA; Batia Wiesenfeld, PhD; Beatrix Brandfield-Harvey, BS; Zoe Jonassen, PhD; Soumik Mandal, PhD; Elizabeth R. Stevens, PhD; Vincent J. Major, PhD; Erin Lostraglio, BA; Adam Szerencsy, DO; Simon Jones, PhD; Yindalon Aphinyanaphongs, MD, PhD; Stephen B. Johnson, PhD; Oded Nov, PhD; Devin Mann, MD

Abstract

IMPORTANCE Virtual patient-physician communications have increased since 2020 and negatively impacted primary care physician (PCP) well-being. Generative artificial intelligence (GenAI) drafts of patient messages could potentially reduce health care professional (HCP) workload and improve communication quality, but only if the drafts are considered useful.

OBJECTIVES To assess PCPs' perceptions of GenAI drafts and to examine linguistic characteristics associated with equity and perceived empathy.

DESIGN, SETTING, AND PARTICIPANTS This cross-sectional quality improvement study tested the hypothesis that PCPs' ratings of GenAI drafts (created using the electronic health record [EHR] standard prompts) would be equivalent to HCP-generated responses on 3 dimensions. The study was conducted at NYU Langone Health using private patient-HCP communications at 3 internal medicine practices piloting GenAI.

EXPOSURES Randomly assigned patient messages coupled with either an HCP message or the draft GenAI response.

Small WR, Wiesenfeld B, Brandfield-Harvey B, et al. Large Language Model–Based Responses to Patients' In-Basket Messages. *JAMA Netw Open*. 2024;7(7):e2422399. doi:10.1001/jamanetworkopen.2024.22399

Key Points

Question Can generative artificial intelligence (GenAI) chatbots aid patient–health care professional (HCP) communication by creating high-quality draft responses to patient requests?

Findings In this cross-sectional study of 16 primary care physicians' opinions on the quality of GenAI- and HCP-drafted responses to patient messages, GenAI responses were rated higher than HCPs' for communication style and empathy. GenAI responses were longer, more linguistically complex, and less readable than HCP responses; they were also rated as more empathetic and contained more subjective and positive language.

Other Generative AI Tools

- Generative AI can detect SDOH risk factors better than ICD codes
- Most SDOH content is in free text

Large language models to identify social determinants of health in electronic health records

[Marco Guevara](#), [Shan Chen](#), [Spencer Thomas](#), [Tafadzwa L. Chaunzwa](#), [Idalid Franco](#), [Benjamin H. Kann](#), [Shalini Moningi](#), [Jack M. Qian](#), [Madeleine Goldstein](#), [Susan Harper](#), [Hugo J. W. L. Aerts](#), [Paul J. Catalano](#), [Guergana K. Savova](#), [Raymond H. Mak](#) & [Danielle S. Bitterman](#) [✉](#)

[npj Digital Medicine](#) 7, Article number: 6 (2024) | [Cite this article](#)

22k Accesses | 20 Citations | 206 Altmetric | [Metrics](#)

Abstract

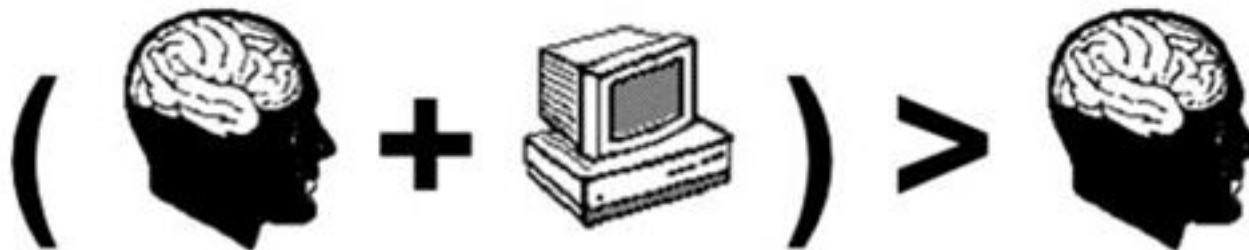
Social determinants of health (SDoH) play a critical role in patient outcomes, yet their documentation is often missing or incomplete in the structured data of electronic health records (EHRs). Large language models (LLMs) could enable high-throughput extraction of SDoH from the EHR to support research and clinical care. However, class imbalance and data limitations present challenges for this sparsely documented yet critical information. Here, we investigated the optimal methods for using LLMs to extract six SDoH categories from narrative text in the EHR: employment, housing, transportation, parental status, relationship, and social support. The best-performing models were fine-tuned Flan-T5 XL for any SDoH mentions (macro-F1 0.71), and Flan-T5 XXL for adverse SDoH mentions (macro-F1 0.70). Adding LLM-generated synthetic data to training varied across models and architecture, but improved the performance of smaller Flan-T5 models (delta F1+0.12 to +0.23). Our best-fine-

Guevara, M., Chen, S., Thomas, S. *et al.* Large language models to identify social determinants of health in electronic health records. *npj Digit. Med.* 7, 6 (2024). <https://doi.org/10.1038/s41746-023-00970-0>

Summary

Summary

- Generative Artificial Intelligence tools will augment provider workflows. Clinicians who do not use AI will become more burdened by healthcare demands.
- Understand the limitations of the Gen Artificial Intelligence tools. Providers are currently responsible for the outputs.



Source: What is Clinical Informatics? Association for Academic Surgery
<https://www.aasurg.org/blog/what-is-clinical-informatics/>

References (Duplicate this slide to create as many slides as you need for your citations while maintaining font guidelines below.)

- Small WR, Wiesenfeld B, Brandfield-Harvey B, et al. Large Language Model–Based Responses to Patients’ In-Basket Messages. *JAMA Netw Open*. 2024;7(7):e2422399. doi:10.1001/jamanetworkopen.2024.22399
- Guevara, M., Chen, S., Thomas, S. *et al*. Large language models to identify social determinants of health in electronic health records. *npj Digit. Med.* 7, 6 (2024). <https://doi.org/10.1038/s41746-023-00970-0>

Thank you!

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