

Learn

Al and Healthcare Delivery: Navigating the Clinical Reality and Expectations

March 26, 2024

Association of American Medical Colleges

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AI & Healthcare Delivery: Navigating the Clinical Reality and Expectations



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Disclosures



Dr. Rehman has funding for research studies by VA and NIH

 Opinion expressed in this presentations are not official statements of the Department of Veterans Affairs or Federal Government but only represent Dr. Rehman's view



AI is not utilized for the preparation of this presentation





ChatGPT (Chat Generative Pretrained Transformer), OpenAI's chatbot powered by artificial intelligence (AI), has become the fastest-growing Internet application in history

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Hu K. ChatGPT sets record for fastest-growing user base — analyst note. Reuters. February 2, 2023



Doom and Gloom

- "Hallucination"
- Implications for patient privacy
- Risk of biases (due to faulty source data)
- Tesla Crashed to autopilot features
- Microsoft's AI chatbot turned sexist & racist
- Amazon's AI recruiting tool showed bias against women
- False facial recognition match leads to Black man's arrest



Beam AL, Drazen JM, Kohane IS, Leong T-Y, Manrai AK, Rubin EJ. Artificial intelligence in medicine. N Engl J Med 2023;388:1220 <u>AI Gone Wrong: 5 Biggest AI Failures Of All Time - Jumpstart Magazine</u>







"The end of the college essay," and medical school personal statements.

Chatbots intended to replace physicians for some medical encounters will imminently be commercially available.







Major health care companies are partnering with technology firms to deploy AI widely and rapidly throughout the U.S. health care system, including by integrating it into electronic health records and voicerecognition software.







We, the medical education as a system, should lead the way when it comes to integrating AI into clinical practice, teaching and research







Role of Al in Healthcare





https://www.linkedin.com/pulse/role-ai-healthcare-infosense-ai/



Examples of AI Uses



- Online Scheduling/Registration/Payment/Check-in
- Chatbots
- Symptom Triage
- Wait-time estimations
- Video Visits
- AI Enabled Medical Coding
- AI built to forecast demand on facilities Supplies, staffing
- Prior Authorizations





AI Applications



Facilitate Diagnosis Predict Pathology Risk Stratify Patients Enhance Practice Management Imaging Applications (prosthetics, surgical planning, disease predicting)



Enhancing Surgical Aide



VA's AI Solutions to Address Burnout Among Health Care Workers



- VA's health care professionals provide lifesaving and life-changing care for Veterans every day.
- <u>Reducing burnout among health care workers</u> is a top priority for VA, especially at a time when VA is delivering more care and more benefits to more Veterans than ever before.
- The Tech Sprint is a part of <u>President Biden's new executive order</u> on safe, secure, and trustworthy artificial intelligence



And VA's efforts to use <u>trustworthy Al solutions</u> to improve health care and benefits for Veterans, their families, caregivers, and survivors.







- These AI scribes will *listen in* to the conversation, and piece together the note but also suggest billing codes, diagnoses, and orders based on where conversation goes. This takes Clinical Decision Support (CDS) to another level.
- The Ambient Dictation for Clinical Encounters track focuses on speech-to-text solutions that can be used to automatically take notes for both the doctor and their patient and upload key excerpts to medical files.







Document Processing Track

The Community Care Document Processing track looks for an AI tool that can reduce the time needed to integrate non-VA medical records into patients' VA records in an easy to access way.









- An FDA-approved system that aids in detecting concerning polyps during colonoscopies, leading to a 50% reduction in missed colorectal polyps compared to standard procedures.
- The VA has deployed these cutting-edge artificial intelligence devices for over 100,000 colonoscopies at 106 facilities to improve the detection and removal of precancerous polyps.
- VA funded purchases of GI Genius at an approximate cost of \$19 million over the past few years, with deployment targeted to complete by the Fall of CY24.







The Recovery Engagement and Coordination for Health - Veterans Enhanced Treatment (REACH VET)

REACH VET initiative uses AI to identify Veterans who are in the top risk tier of predicted risk for suicide.

• **REACH VET reviews** data from the prior two years of VHA health care services to identify at-risk Veterans.

• Since the program began in 2017, REACH VET has identified more than 117,000 VHA patients.









 Consistent monitoring of performance indicators show that evaluation and outreach occur for almost all of these patients.

 Inclusion in REACH VET is found to be associated with improved suicide prevention.





Improved Suicide Prevention



- These improvements include
 - Increased receipt of completed outpatient appointments,
 - Fewer documented suicide attempts,
 - Fewer inpatient mental health admissions,
 - Fewer emergency department days
 - And greater completion of new suicide prevention safety plans.







AI and UME

 Medical students are already starting to apply AI in their learning.

Faculty are contemplating how AI can help them design courses and evaluations.



Cooper, Avraham; Rodman, Adam. Al and Medical Education — A 21st-Century Pandora's Box. N Engl J Med 2023; 389:385-387





UME's Dual Challenge

- Teach students how to utilize AI in their practice
- Adapt to the emerging academic use of AI by students and faculty.
- Medical school curriculum built by humans is now in doubt:
 - How will a medical school provide quality control for components of its curriculum that didn't originate from a human mind?
- How can schools maintain academic standards if students use AI to complete assignments?









Curricular standards to integrate AI?

Al Generated Curriculum?

Shouldn't these then be rigorously assessed, peer-reviewed and published?



Russell RG, Lovett Novak L, Patel M, et al. Competencies for the use of artificial intelligence-based tools by health care professionals. Acad Med 2023;98:348-356.



Graduate Medical Education (GME)



Prepare for a future in which AI tools are integral components of their independent practice.

- Residents and fellows have 30 to 40 years of practice ahead of them and will need to adjust to evolutions in clinical care.
- Trainees will have to become comfortable working with AI and will have to understand its capabilities and limitations, both to support their own clinical skills and because their patients are already using it.







Al-Powered Patients

ChatGPT can produce advice on cancer screening in patient-friendly language, though not with 100% accuracy.

Will AI powered patients start a revolution of the patient-doctor relationship?







Accreditation Council for Graduate Medical Education

Currently have no formal policies on AI

Al education into common program requirements?

Which would compel programs to make changes to their training approaches.













Data and Analytics Steering Committee

March 26, 2024

Al and Governance



Governance Structure

Data and Analytics Steering Committee (Strategic Decision Making, Prioritization, & Vision)

Data Governance Council (Policies, Procedures, Standards & Guidelines)





Analytics Intervention Unit (AIU) Goals

- 1. **Optimize clinical outcomes** through the implementation of predictive tools that have clear clinical and operational interventions through application of model data.
- 2. Identify clear priority areas for the medical center where predictive analytics may enhance decision-support.
- **3. Support collaboration** among clinical, research, administrative and ancillary support staff across the health system and university, in the development, evaluation and deployment of predictive analytic initiatives.
- 4. Serve as a valuable resource to model developers and provide expertise in clinical informatics, data science, and health system technology/architecture.
- 5. Deliver safe and effective predictive software functionality that improves the patient care.
- 6. Develop and refine evaluation criteria for models entering hospital operations.
- 7. Monitor and ensure data utilized for each model in UChicago Medicine production is validated on an on-going basis.
- 8. Serve as a national leader in predictive model planning, development and deployment in healthcare delivery.



AIU Scope

- Provides subject matter expertise
- Provides strategic direction and operational support for all predictive and interventional models that impact patient care from development to deployment
- Is an advisory body, but it is empowered to reject unsafe models

Inclusion:

- » Predictive tools including, but not limited to, those that treat, diagnose, cure, mitigate, or prevent disease or other conditions
- » All predictive and prescriptive tools intended for implementation at UChicago Medicine to support healthcare delivery
- » Models that align with patient quality of care and patient safety goals

Exclusion:

- » Models without a direct patient care component
- » Research models that will not be implemented for patient care



AIU Membership

Core (~10 people)

- Clinical Operations
- Data Analyst/Scientist
- IT Systems Engineer
- Frontline Staff
- Diversity, Equity & Inclusion

Ad-hoc

Operations Unit / SME



Where do Al tools come from?



Buy, Partner, or Build?



Accounting for the Limitations of Al

- Understanding training sets of models
- Testing for bias
- Continuously validating outcomes



Model Life Cycle





Example: Validation of 6-month mortality model

- Model development internally in collaboration with the Palliative Care group to predict the probability of patient mortality within 6 months
- Updating existing model, as previous model trained before COVID and before system expansion

Validation Check	Description
Comparing Train and Test	Hospital data can have time dependence therefore check that features appear similarly in the train and test data.
Trends in False Negatives	For this model minimize false negatives (model predictions that a patient will live but they die within 6 months). Reviewed characteristics of those patients to ensure no bias.
Specificity in Imputed Lab Values	Model inputs cannot have missing values so missing values are imputed (typically using mean or median). However for lab values the population mean or median may have a bias based on the motivation for the order. Analysis validated imputed lab values where within normal reference range.
Percentage of Missing Values	The percentage of encounters with missing values for each feature was made. This is especially important to track over time (ex: Sunquest to Beaker lab system change).
Comparison to eCART	Compared scores and outcomes against eCART, which identifies patient deterioration within the encounter.
New Context	Evaluated if a Covid-flag would improve results. It is important to consider other model features based on new external factors (ex. Covid) or new clinical markers that may increase the model performance.


Focus for 2024

Governance and increased transparency

- Develop procedures and standards for each model work flow step
- Example: Documentation standards for model validation

Implement a central model monitoring system

• Collaboration with data science, business intelligence, analytics engineering, UCMIT

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			Louise Heelan	
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Demonstrated experience: Metric monitoring for



By the Numbers

Stage	# of models	Details
In queue	5	 Scheduling Template (IVTH Silver Cross, IVTH River East) Total Joint Arthroplasty Risk Assessment Lab Draws Epic Falls Model for Ingalls
In development or validation	3	 Scheduling Template IVTH DCAM re-optimization 6-month mortality No Show
In production	14	 Orland Park Infusion Scheduling Template Acute Stroke Risk Predictor AKI Risk Algorithm eCART IVTH DCAM Infusion Scheduling HOSPITAL score Epic General Risk Score Epic Fall Risk Peds Nationwide Sepsis 6 month mortality Chorio Re-hospitalization Oncology Readmission Risk Score pCART
Turned off	5	 Operating Room Nurse Assignment Model MRI Scheduling Epic Remaining Length of Stay (LOS) Internal Length of Stay (LOS) LACE+



AI in Medical Education

FY25 Initiatives:

- Ambient Listening
- Template standardization for documentation



Appendix



Process Map





Model Deployment Process

Intake; Determine and Align on Clinical Priorities	Source and Develop (for models that have not yet been built)	Review and Validate	Test, Deploy and Communicate	Monitor Results and Effectiveness
Identify areas of need / priority where predictive data may provide clear steps for clinical intervention	Identify external sources for model procurement or development	Review the scientific validity and operational value of each model to be implemented	Conduct integration / interface development Validate within Epic or other deployment	Track on-going results and clinical effectiveness metrics Conduct periodic
Determine whether implementation aligns with the goal of delivering safe, effective care	OR Develop model internally with UCM data	Provide feedback and acceptance, rejection or concerns for deployment	system Identify appropriate security and access Shift model to full production Training and communication to stakeholders	review and evaluation of clinical outcomes as a result of predictive data



AI: The Resident Perspective

Tauhid Mahmud MD MPH Stony Brook Medicine



I have no actual or potential conflict of interest in relation to this program/presentation.

Disclosures



Agenda







Levels of AI Engagement Observers

Peripherally aware of AI and institutional AI initiatives

Some firsthand experience with AI tools

Pragmatic approach to incorporating Al into their work

nnovators

Participate in research projects to develop and validate new AI models

Provide clinical expertise to inform the development of Al algorithms.

Advocate for the use of Al in their specialty and educate peers on potential applications.

Ambient Al Scribe Initiative

Annual Family Medicine Update

Levels of AI Engagement Observe

Peripherally aware of AI and institutional AI initiatives

Adopters

Use AI-powered tools for tasks such as patient education, lab order templates, and drafting letters

Innovators

Participate in research projects to develop and validate new AI models

Provide clinical expertise to inform the development of Al algorithms.

Advocate for the use of Al in their specialty and educate peers on potential applications.

Some firsthand experience with Al

Pragmatic approach to incorporating AI into their work

Prev Med Board Buddy 🗸	Q	~d 💌 🛋 🎯
	۲	Please write a short note to my patient explaining why we can't give them fluids during a CHF exacerbation.
Event Med Board Buddy By Tauhid Mahmud A An assistant for ACPM board exam prep, clarifying concepts and offering study strategies.	ŝ	 Subject: Understanding Fluid Restriction in CHF Exacerbation Dear [Patient's Name], I hope this message finds you well. I am writing on behalf of Dr. [Doctor's Name] to explain why we can't provide you with excess fluids during an exacerbation of your Congestive Heart Failure (CHF). In CHF, your heart struggles to pump blood efficiently, which can lead to buildup of fluid in your body, especially in the lungs and lower extremities. This excess fluid can worsen your symptoms, leading to difficulty in breathing, swelling (edema), and other complications. During a CHF exacerbation, your condition becomes more unstable, and it is crucial to carefully manage your fluid intake to prevent further strain on your heart. Providing additional fluids during this time could exacerbate your symptoms and potentially lead to a serious condition known as acute pulmonary edema, which can be life-threatening. We understand that this may be challenging, but it is an essential part of managing your condition. We recommend you to adhere to the prescribed fluid restriction, take your medications as directed, and monitor your weight daily. Please do not hesitate to contact us if you have any questions or concerns. Your health and well-being are our utmost priority. Best regards, Tarthid Mahmurd MD
Quiz me on epidemiology topics. Quiz on USPSTF Guidelines		Regenerate
Motivational Interviewing Cases Quiz on CPSTF Guidelines		Open Prompt Library
Message Prev Med Board Buddy	Тар	o on prompt library or type here.

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Levels of AI Engagement Obse

Peripherally aware of Al and institutional A initiatives Use AI-powered tools for tasks such as patient education, lab order templates, and drafting letters

Innovators

Participate in research projects to develop and validate new AI models

Provide clinical expertise to inform the development of Al algorithms.

Advocate for the use of Al in their specialty and educate peers on potential applications.

Some firsthand experience with Al

Pragmatic approach to incorporating Al into their work

The Role of Natural Language Processing in Primary Care: A Scoping Review

Make Private Public 20 1.7MB Contributors: Tauhid Mahmud, Laurel Scheinfeld, Lyncean Ung, Jonathan Ambut, Dipika Rana, Tejas Patel, Sritha Rajupet Date created: 2023-12-12 09:40 PM | Last Updated: 2024-02-09 10:23 PM Create DOI Category: 📦 Project Description: Scoping review focused on the intersection of natural language processing and primary care. License: Add a license Wiki Primary research question(s) What is the scope of research on the application of NLP technologies in primary care settings, and what are the key themes and methodologies identified in this body of literature? Type of review

The proposed scoping review will be conducted in accordance with the Joanna Briggs Institute (JBI) methodology for scoping reviews and presented in the format as suggested by P...

Additional Projects:

- Utilizing natural language processing models for radiology reports
- Thinking through clinical AI infrastructure on new databases
- Comparing AI readouts to academic reviewers of journal articles

Incorporating AI into Medical Education

- Premed
 - Undergraduate and graduate degree students are already regularly engaging with AI
 - Personal statement writing
 - Interview preparation
- Medical Schools
 - University of Texas: Doctor of Medicine (M.D.) and Master of Science in Artificial Intelligence (M.S.A.I.) will form a five-year M.D./M.S.
 - Students are building tools

Incorporating AI into Medical Education

Graduate Medical Education

- Morning Report / Noon Lectures
- Conferences
- Online workshops and webinars
- Research Electives with Informatics Department
- Review Articles
- Model building

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Radiologic Resident Education

AI-RADS: An Artificial Intelligence Curriculum for Residents

Alexander L. Lindqwister, Saeed Hassanpour, Petra J. Lewis, Jessica M. Sin

Rationale and Objectives: Artificial intelligence (AI) has rapidly emerged as a field poised to affect nearly every aspect of medicine, especially radiology. A PubMed search for the terms "artificial intelligence radiology" demonstrates an exponential increase in publications on this topic in recent years. Despite these impending changes, medical education designed for future radiologists have only recently begun. We present our institution's efforts to address this problem as a model for a successful introductory curriculum into artificial intelligence in radiology titled AI-RADS.

Materials and Methods: The course was based on a sequence of foundational algorithms in AI; these algorithms were presented as logical extensions of each other and were introduced as familiar examples (spam filters, movie recommendations, etc.). Since most trainees enter residency without computational backgrounds, secondary lessons, such as pixel mathematics, were integrated in this progression. Didactic sessions were reinforced with a concurrent journal club highlighting the algorithm discussed in the previous lecture. To circumvent often intimidating technical descriptions, study guides for these papers were produced. Questionnaires were administered before and after each lecture to assess confidence in the material. Surveys were also submitted at each journal club assessing learner preparedness and appropriateness of the article.

Results: The course received a 9.8/10 rating from residents for overall satisfaction. With the exception of the final lecture, there were significant increases in learner confidence in reading journal articles on AI after each lecture. Residents demonstrated significant increases in perceived understanding of foundational concepts in artificial intelligence across all mastery questions for every lecture.

Conclusion: The success of our institution's pilot AI-RADS course demonstrates a workable model of including AI in resident education.

Key Words: Artificial intelligence; Education; Residency training; Machine learning; Radiology.

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Abbreviations: AI Artificial Intelligence, ML Machine Learning

Lindqwister AL, Hassanpour S, Lewis PJ, Sin JM. Al-RADS: An Artificial Intelligence Curriculum for Residents. Acad Radiol. 2021 Dec;28(12):1810-1816. doi: 10.1016/j.acra.2020.09.017. Epub 2020 Oct 16. PMID: 33071185; PMCID: PMC7563580.

Lindqwister AL, Hassanpour S, Lewis PJ, Sin JM. AI-RADS: An Artificial Intelligence Curriculum for Residents. Acad Radiol. 2021 Dec;28(12):1810-1816. doi: 10.1016/j.acra.2020.09.017. Epub 2020 Oct 16. PMID: 33071185; PMCID: PMC7563580.

Future Direction

Regardless of the level of engagement, trainees are considering the role of AI in their clinical future.

Institutions should meet trainees and learners where they are to promote AI engagement.

"It is clear to me that AI will never replace physicians — but physicians who use AI will replace those who don't."- Dr Jesse Ehrenfeld, AMA President

Thank you

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Thank you!

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