


The Future of Oncology: How AI Will Shape the Next Decade

Ravi B. Parikh, MD, MPP
Associate Professor of Medicine
Department of Hematology and Medical Oncology
Emory University School of Medicine

Transforming Oncology Care Through Medically Integrated Collaboration




1


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2

OBJECTIVES

1. Define artificial intelligence and related concepts in oncology practice
2. Identify discrete use cases of AI in treatment decision-making and clinical decision-support
3. Recognize ethical or methodological challenges surrounding the use of AI
4. Discuss concrete next steps to facilitate responsible use of AI within health care settings

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3

DISCLOSURES

The following relevant financial relationships from the past 24 months have been identified and disclosed for the following faculty of this CE activity:

- Ravi B. Parikh, MD, MPP
 - Grants from the National Institutes of Health, Department of Defense, Prostate Cancer Foundation, National Palliative Care Research Center, NCCNO Foundation, Conquer Cancer Foundation, Humana, Emerson Collective, Schmidt Futures, Arnold Ventures, Mendel.ai, and Veterans Health Administration; Personal fees and equity from GNS Healthcare, Thyme Care, and Onc.AI; Personal fees from the ConcertAI Cancer Study Group, Mendel.ai, Biofourm, Archetype Therapeutics, Credence, C1 Therapeutics, Humana, and Nanology; Honoraria from Flatiron and Medscape; Has board membership (unpaid) at the Coalition to Transform Advanced Care and American Cancer Society; Editor at the Journal of Clinical Oncology; and serves on a leadership consortium (unpaid) at the National Quality Forum, all outside the submitted work.

There are no relevant conflicts of interest to disclose for this presentation for the following planners of this CE activity:

- Apiwe Ojulu, PharmD, MS
- Daisy Doan, PharmD

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4

My first experience with AI...

First Name	Last Name	Role	Organization	Reimbursement	Reimbursement Type	Reimbursement Amount	Reimbursement Period	Reimbursement Source
JENNIFER	BERG	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
ANDREW	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
BLAKE	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
CHRISTOPHER	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
DAVID	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
EMILY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
FRANK	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
GRACE	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
HENRY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
ISABEL	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
JACK	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
JANE	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
JOHN	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
JULIA	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
KARL	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
LARRY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
MARY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
NANCY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
OLIVER	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
PETER	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
QUINN	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
Rachel	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
SEAN	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
TERESA	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
THOMAS	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
URSULA	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
VICTOR	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
WILLIAM	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
Xavier	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
YVONNE	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson
ZACHARY	WILLIAMS	MD	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson	MD Anderson

Disclaimer: Authors' own mockup, no real patient names

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5

Definitions

Artificial intelligence (AI):
Systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.¹

Autonomous AI:
AI systems that can operate independently, analyze data, make decisions, and execute tasks without constant human oversight.

Assistive AI:
AI systems that support human users by providing information, suggestions, or assistance in completing tasks.

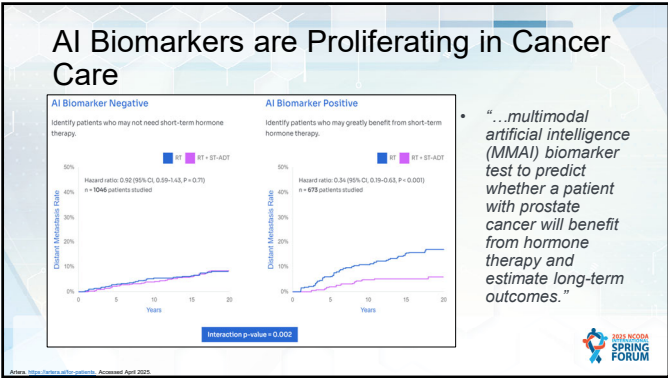
Generative AI:
AI systems that can create new content rather than simply analyzing or categorizing existing information

Large Language Models:
AI systems trained on vast amounts of text data to understand and generate human language

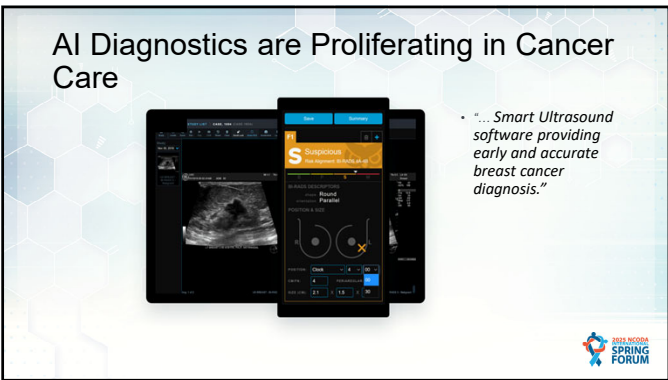
1. European Commission: "A Definition of Artificial Intelligence"

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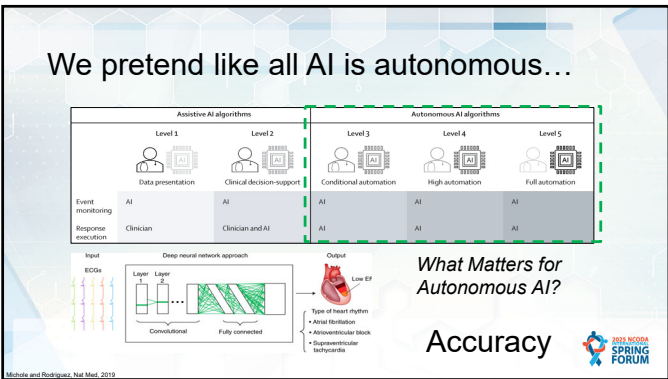
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7



8




9

...when instead most current AI is assistive

Assistive AI algorithms			Autonomous AI algorithms		
Level 1	Level 2		Level 3	Level 4	Level 5
Data presentation	Clinical decision support		Conditional automation	High automation	Full automation
Event monitoring	AI		AI	AI	AI
Response execution	Clinician	Clinician and AI	AI	AI	AI

What Matters for Assistive AI?

Trust




10

Poll

You are an oncology pharmacist. What percentage of your daily pharmacy workflow do you believe could be partially or completely automated by AI tools in the next 3 years?

- a. Less than 10%
- b. 10-25%
- c. 26-50%
- d. 51-75%
- e. More than 75%




11

Poll

In your experience, which part of oncology medication management would benefit most from AI support?

- a. Drug interaction checking across complex regimens
- b. Identifying candidates for dose modification
- c. Oral oncology therapy monitoring and adherence
- d. Supportive care optimization
- e. Inventory management and cost optimization



12


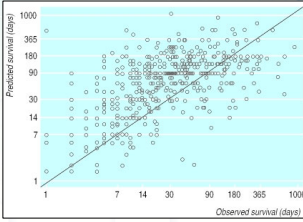
Examples of Successful Implementation of AI in Oncology Practice



13

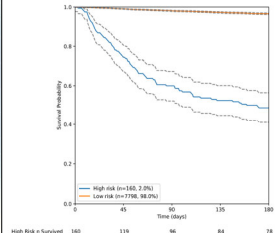
Use Case: Serious Illness Communication

- Early communication is key to reducing oncology patient experience
 - Reduced end-of-life utilization
 - Reduced anxiety and depression
 - Improved caregiver satisfaction
- Identifying appropriate patients is key, but there is a lack of clarity in prognosis
 - Oncologists overestimate survival by 5.4x



14

Developing the Algorithm



Clinician perspectives on machine learning prognostic algorithms in the routine care of patients with cancer: a qualitative study

Machine Learning Approaches to Predict 6-Month Mortality Among Patients With Cancer

JAMA Oncology | Original Investigation
Validation of a Machine Learning Algorithm to Predict 180-Day Mortality for Outpatients With Cancer

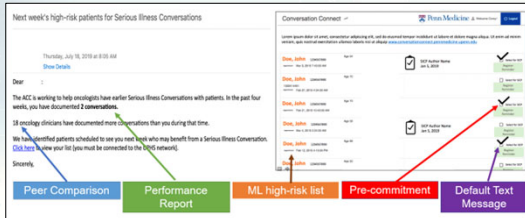
Variables	Examples	Features
Demographics	Age, Gender	
Comorbidities	33 Elixhauser comorbidities	• Total count • Recent*
Cancer-specific	Stage, tumor markers	• Total count • First/last value • Min/Max
Laboratories	CMP, CBC, LDH	• Proportion ordered STAT
Recent utilization	Outpatient visit number	

1. Perle RB et al. Support Care Cancer. 2022;30(5):1493-1517. 2. Perle RB, et al. JAMA Netw Open. 2019;2(10):e1915587. 3. Moun CR, et al. JAMA Oncol. 2020;6(11):1725-1730.

15

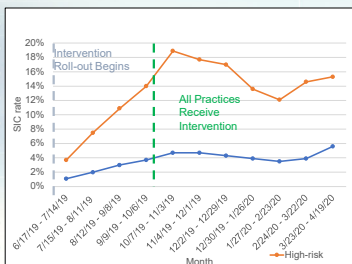
Developing Interfaces to Embed into Clinician Workflow

Use Case: Predicting mortality to prompt more serious illness communication



16

Studying Impact



	Control	Intervention
Chemo last 14 days	10.4%	7.5%
Savings in last month of life	~\$1500	

17

Insights from Clinicians

Population: 25 oncology clinicians (13 high, 12 low responders)

Facilitators:

- Prompting better documentation of conversations in the electronic health record
- Peer comparisons & performance reports
- Validating norms around early conversations

Barriers:


- Cancer-specific heterogeneity in algorithm performance
- Frequency and tone of automated text messages

"In blood cancers, we do so many scheduled admissions and things like stem cell transplants, there are a lot of patients who would have recently been in the hospital twice...So actually, [the algorithm-based lists] were] often inaccurate in terms of who needed to have a discussion ..."

18

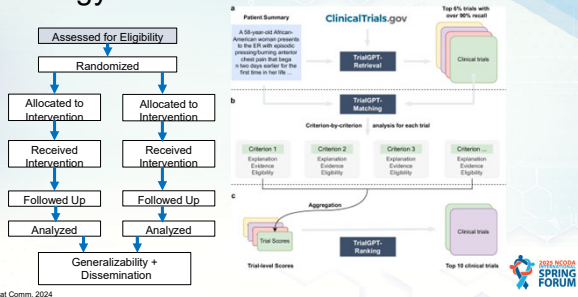
Use Case: Clinical Trial Prescreening

Assess whether Human-AI teams leveraging large language model output can more efficiently and/or accurately extract a set of 13 common clinical criteria from deidentified **unstructured** electronic health records (EHRs)




19

Traditional Clinical Trial Workflow for Oncology Clinical Trials



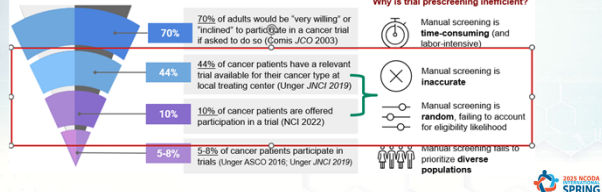
The diagram illustrates the traditional clinical trial workflow and an AI-assisted alternative. The traditional workflow (left) is a linear process: Assessed for Eligibility → Randomized → (Allocated to Intervention / Allocation to Control) → Received Intervention / Received Control → Followed Up → Analyzed → Generalizability + Dissemination. The AI-assisted process (right) involves a Patient Summary (e.g., 'A 58-year-old African American female presents to the ER with symptoms...') being processed by 'TrueNLP: Ranked' to identify 'Top 6% trials with most 80% match'. This leads to 'TrueNLP: Matching' and 'Criteria-by-criteria analysis for each trial' across four criteria: Criterion 1 (Exploration, Evidence, Eligibility), Criterion 2 (Exploration, Evidence, Eligibility), Criterion 3 (Exploration, Evidence, Eligibility), and Criterion 4 (Exploration, Evidence, Eligibility). This results in 'Trial Scores' and 'Total Trial Scores', which are then ranked by 'TrueNLP: Ranking' to identify 'Top 10 clinical trials'.




20

Prescreening is a Key Bottleneck for Cancer Trials

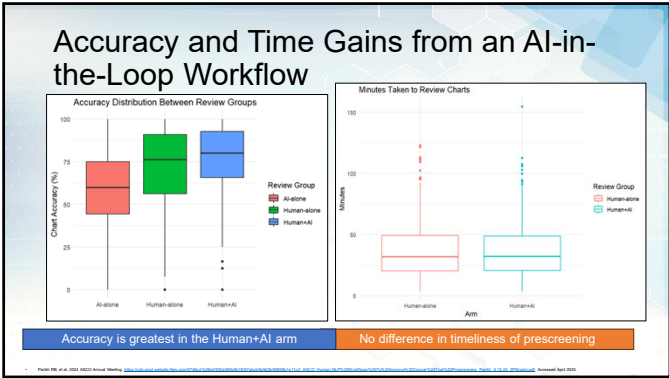
- Only **5-8%** of adult cancer patients participate in trials, with many subpopulations underrepresented
- Yet **55%** of adult cancer patients do participate when offered a trial (Unger et al., JNCI 2021)



The infographic uses a funnel to show the attrition of potential participants. It starts with 70% of adults being 'very willing' or 'inclined' to participate (Cohen, JCO 2003). This drops to 44% of cancer patients having a relevant trial available at their local center (Unger JNCI 2019). Then, 10% of cancer patients are offered participation in a trial (JNCI 2022). Finally, only 5-8% of cancer patients participate in trials (Unger ASCO 2016; Unger JNCI 2019). A section titled 'Why is trial prescreening inefficient?' lists three reasons: Manual screening is time-consuming (and labor-intensive), Manual screening is inaccurate, and Manual screening is random, failing to account for eligibility likelihood. A final note states: 'Manual screening fails to prioritize diverse populations'.



21



25

Criteria-Specific Accuracy

	Criteria	Accuracy (%)			p-value
		Human- Alone	Human + AI	AI- Alone	
Biomarker	Was Biomarker Tested?	84.6	93.2	88.1	<0.001*
	Categorical Value	67.9	79.0	32.5	<0.001*
	Interpretation	80.8	91.3	35.7	<0.001*
Neoplasm	Cancer Type	86.9	86.4	73.3	0.797
	Stage Group	71.7	73.4	57.0	0.573
	M Stage	43.9	57.0	60.2	<0.001*
	N Stage	50.5	66.3	52.6	<0.001*
	T Stage	56.3	71.6	54.3	<0.001*
Other	Outcome	23.7	35.9	58.2	0.004*
	Response	47.1	51.7	60.4	0.195
	ECOG Status	84.7	78.1	34.4	0.096
	Medication Concept	89.0	89.1	59.4	0.915

26

Poll

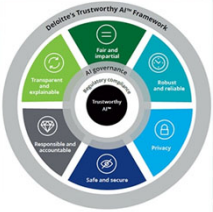
You have just seen 2 examples of clinical decision support in oncology practice. In your oncology pharmacy practice, which of the following AI applications would be most valuable to implement?

- a. Automated chemotherapy dosing recommendations based on patient-specific factors
- b. Prediction of adverse events from specific drug combinations
- c. Clinical trial matching for patients with rare genomic alterations
- d. Medication adherence tracking and personalized interventions
- e. None of the above

27


Principles of Trustworthy AI

CHAI Releases Recommendations for Trustworthy AI in Health



* Coalition for Health AI (CHAI). https://chai.org/wp-content/uploads/2024/03/Blueprint-for-trustworthy-ai_v1.0-2.pdf. Accessed April 2025.

* Details: <https://news2.definitive.com/news/pages/definitive-analytic-solutions/office-of-ai-framework.html>. Accessed April 2025.

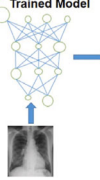


28

Explainability

Trained Model

Inference



Without Explainability

Prediction

- Cardiomegaly
- Confidence 78%

Unanswered

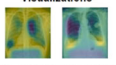
- How are the predictions made?
- Why is the prediction correct?
- Why is the prediction incorrect?
- Which features affected this prediction?

With Explainability


Text

The lungs exhibit cardiomegaly with a large silhouette of the heart.

Visualizations



Example Images



Example Models

Increased heart silhouette size?

Cardiomegaly

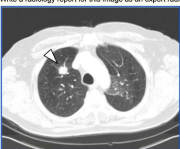
Other

29

When explainability goes wrong...

Prompt:

Write a radiology report for this image as an expert radiologist.



GPT-4V:

Report:

Date: 6/25/2021


Study Type: Chest CT

Subject: 42-year-old male

Findings: The chest CT images demonstrate a nodular opacity in the left upper lobe, measuring approximately 1.3 cm in diameter. The opacity appears to have spiculated margins and is located adjacent to the pleura. There is no evidence of mediastinal or hilar lymphadenopathy.

Impression: The findings are concerning for a primary lung malignancy. Further evaluation with a biopsy is recommended to confirm the diagnosis.

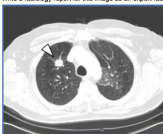
* Yang et al. w/NC. 2023. "The Dawn of LLMs: Preliminary Explorations with GPT-4V [poster]"



30

When explainability goes wrong...


Prompt:
Write a radiology report for this image as an expert radiologist.



GPT-4V:
Report:
Date: 6/23/2021
Study Type: Chest CT
Subject: 62-year-old male
Findings: The chest CT images demonstrate a nodular opacity in the **left upper lobe**. **Impression: approximately 1.4 cm in diameter.** The opacity appears to have spiculated margins and is located adjacent to the pleura. There is **evidence of mediastinal lymphadenopathy.**
Impression: The findings are concerning for a primary lung malignancy. Further evaluation with a biopsy is recommended to confirm the diagnosis.

Evaluation from Professionals:
Correct study type and identification
Mentioned nodule **but in the left rather than in the right**
(One measurement (diameter))

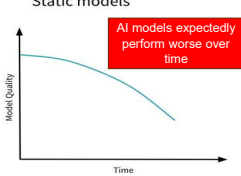
Yang et al. arXiv, 2023. "The Dawn of LLMs: Phenomenal Explainability with GPT-4 Vision"



31

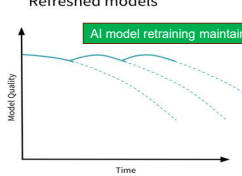
Reliability in AI Models

Static models



AI models expectedly perform worse over time


Refreshed models



AI model retraining maintains accuracy

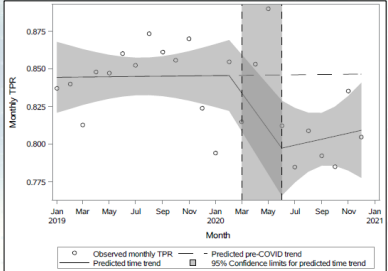
Proactive monitoring can prevent expected performance drift

Star S. <https://medium.com/data-science/ai-models-for-real-world-scenarios-9fc926322246>. Accessed April 2025.




32

Performance Drift in Mortality Prediction AI



- AI models notably “drifted” during the COVID pandemic
- Many of these models failed to return to normal until well into the pandemic

Parikh et al. JAMA, 2023. TPR = True positive rate



33

Bias in AI Algorithms

- Biases in Electronic Health Record Data due to Processes within the Healthcare System: Retrospective Observational Study
 - Biased data generation → biased algorithms
- Health Care Segregation, Physician Recommendation, and Racial Disparities in BRCA1/2 Testing Among Women With Breast Cancer
 - Likelihood of genetic testing among African-American women with breast cancer

Analysis	Odds Ratio (95% CI)
Overall	0.40 (0.34-0.48)
Adjusted for mutation risk	0.66 (0.53-0.81)
Adjusted for physician recommendation	0.76 (0.57-1.02)

"The presence of a laboratory test order, regardless of any other information about the test result, has a significant association ($P<0.001$) with the odds of survival in 233 of 272 (86%) tests."

• McCarthy et al. J Clin Oncol. 2016; 34 (22): 2610-2618; Agniet al. BMJ. 2018;361:k1479

34

Can AI Mitigate Disparities?

	Pre-intervention, %	Post-intervention, %	Absolute Percentage-point Difference
Non-Hispanic White	3.9 (58/1494)	14.2 (201/1417)	10.3
Non-Hispanic Black	3.6 (17/467)	16.9 (69/408)	13.3
Other*	1.2 (2/164)	19.5 (34/408)	18.3

In a trial of a machine learning-based nudge to perform end-of-life conversations, there was a significantly higher impact for non-White minorities

• Parikh et al. JAMA Onc. 2023

35

Poll

Which barrier do you see as most significant to implementing AI in oncology pharmacy practice?

- a. Cost of implementation and maintenance
- b. Integration with existing electronic health record systems
- c. Liability concerns and unclear accountability
- d. Lack of pharmacy-specific AI training and expertise
- e. Patient/provider acceptance of AI recommendations


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36

SUMMARY

- **AI in Oncology:** AI applications can be assistive or autonomous, with most current applications being assistive
- **Proven Use Cases:** AI systems have demonstrated value in decision support and augmenting human processes
- **Core Challenges:** Key issues include explainability limitations, algorithmic bias, performance drift over time, and variable accuracy across different cancer types
- **Path Forward:** Responsible implementation requires proactive monitoring, comprehensive model documentation, human-in-the-loop workflows, and transparent integration into clinical processes

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37

QUESTION & ANSWER

The Future of Oncology:
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Ravi B. Parikh, MD, MPP

Associate Professor of Medicine

Department of Hematology and Medical Oncology


Emory University School of Medicine

Ravi.bharat.parikh@emory.edu

www.haclab.org

@ravi_b_parikh

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38

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39
