# "Al For Society Group"

# Objective Approaches in a Subjective Medical World: Investigating Al Integrations in Healthcare Technologies

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# **Objective** Approaches in a **Subjective** Medical World

# Subjective <> Objective Interaction **Human-Al Interaction**

- → i-SDM Framework: Clinical Decision Science [CSCW 23', CSCW 24']
- Patient-centered Shared Decision-Making Tool [CHI 24']  $\rightarrow$
- Explainable AI [CSCW 24']  $\rightarrow$

# Improve Subjective w/ Objective Approaches **Healthcare Intelligence**

- Clinical Decision Support Tool (DST) [Bioinformatics 20', CHI 23']  $\rightarrow$
- → Retrospective Comparison In-Basket Message Study: Human Care Team VS. GPT4o-based [Mayo Proceeding: Digital Med 25']
- → Veterinary Precision Health [AAAI 24', IAAI 25' DAI Workshop]

# CHI 24: i-SDM Frameworks (Al-Based Shared **Decision Making Tool)**



Eli Goldring  $\approx$   $\approx$  3rd+

Executive Director of Business Development at Culinary Depot/Founder of the Hope Organization

**David Lubarsky**, this is a fascinating insight into how AI can bridge the gap for older adults with cancer. It's heartening to see technology being leveraged to empower patients in their treatment decisions, especially for those who might struggle with tech literacy. This could truly transform patient-clinician communication.

#### CLINICAL DAILY NEWS

1w •••

**KRISTEN FISCHER** 



#### Like Reply

1.Y. Hao, Z. Liu, B. Riter, S. Kalantari. Advancing Patient-Centered Shared Decision-Making with AI Systems for Older Adult Cancer Patients. In Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11--16, 2024, Honolulu, HI, USA. https://doi.org/10.1145/3613904.3642353 2.Y. Hao, C. Löckenhoff, H. Lee, J. Zwerling, S. Kalantari. The i-SDM Framework: Developing Al-based Tools in Shared Decision-Making for Cancer Treatment with Clinical Professionals. Companion of the 2024 Computer-Supported Cooperative Work and Social Computing (CSCW 24'). https://doi.org/10.1145/3678884.3681841

# **CORNELL CHRONICLE**

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#### AI may improve doctor-patient interactions for older adults with cancer

By Emily Groff, College of Human Ecology

May 14, 2024



### Report: Al tool could boost communication for older adults with cancer

# **<u>Shared Decision Making (SDM)</u>** Preliminary Ten Important **Factors Selections with 12 Participants (7 Patients + 5 Clinicians**)

Total Participants' Approved Factors ( out of 12 )	12	12	11	10	7	7	6
	2	2	2	2		2	-
	2	2	2	2			
Clinician Participants	2	2	2	2			
( C1 - C5 )	2	2	2	2			
	2	2	2	2		2	2
	2	2	8				2
	2	2	2		2		
	2	2	2	2	2		2
Patient Participants	2	2	2	2	2		2
(	2	2	2	2			8
	2	2	2	2	2	2	2
	2	2	2	2	2	2	2
Ten Important factors for SDM (From high to low)	Survival Rates in 5 years	Potential Risk	Alternative Treatment Options	Average Patient Age for the Treatment	Distance (Treatment Location)	Detailed Treatment Understanding	Total Treatme Duratio



Patient Participant Approved





**Clinician Participant Felt This Option Indifference** 

# **Single** -Diamond Framework for Patient-Centered SDM process





# **Double** -Diamond Framework for Patient-Centered SDM process



option based on their needs and preferences

# i-SDM **Step-wise Process**



ection	IS	
Survival Rates	Select	
Pain Degr	ee	
Average Treatm	ient Age	X
Facility Qu	ality	X
Survival R	ates	
Medical C	ost	

# i-SDM Prototype's Heatmap

Negative Verbal Cues

Positive Verbal Cues

Neutral Verbal Cues

# PMATION

#### **Step 3 Survival Rates**



#### **Step 5 Other Factors**



#### **Step 1 Factor Selections**



#### **Step 2 Basic Information**



#### Step 4 Side Effects

		You n	nav have		
You n Erectile I	nay have	Urinary I	ncontinence	Ot	hers
Sta	rgery	8 25	irgery	Su	dista.
ens	diation 50	0% Ra	100%	Ph.	100%
Ch.		0%	100%	2%	100%
22 I	20	Active St	urveillance	Active S	urveillance
0%	10%	0% More E	xplanation	es.	1074
				_	

#### **Step 6 Finalize Decisions**



# **Cue Labels Analysis** across Steps

316 labels, comprising 145 positive cues labels (45.89%), 73 neutral cues labels (23.10%), and 98 negative cues labels (31.01%).



Patient Participant Labels



# i-SDM Prototype's Heatmap for Evaluating i-SDM Prototype

Negative Verbal Cues

Positive Verbal Cues

Neutral Verbal Cues



# **Reason More != Perform Better?** Investigating the Trade-Off Between **Depth of Reasoning and Performance** in LLMs' Medical Al Reasoning

**E.g.** Iterations, Inference time, **# of step-wise process** 



E.g. Accuracy, Confidence, **Error propagation (overfitting)** 

# PubMedQA

A Dataset for Biomedical Research Question Answering

#### **Question:**

Do preoperative stating reduce atrial fibrillation after coronary artery bypass grafting?

#### **Context:**

(*Objective*) Recent studies have demonstrated that statins have pleiotropic effects, including anti-inflammatory effects and atrial fibrillation (AF) preventive effects [...] (Methods) 221 patients underwent CABG in our hospital from 2004 to 2007. 14 patients with preoperative AF and 4 patients with concomitant valve surgery [...] (*Results*) The overall incidence of postoperative AF was 26%. Postoperative AF was significantly lower in the Statin group compared with the Non-statin group (16%) versus 33%, p=0.005). Multivariate analysis demonstrated that independent predictors of AF [...]

#### **Long Answer:**

(Conclusion) Our study indicated that preoperative statin therapy seems to reduce AF development after CABG. **Answer:** yes



eaderboar	d (reasoning-required s	setting)			
	Model	Code	Size	Accuracy (%)	Macro-F <sub>1</sub> (%)
<b>1</b> Nov 28, 2023	GPT-4 (Medprompt) Microsoft (Nori et al. 2023)		NA	82.0	NA
<b>2</b> May 16, 2023	Med-PaLM 2 Google Research & DeepMind (Singhal et al. 2023)		NA	81.8	NA
3 Nov 27, 2023	MEDITRON EPFL (Chen et al. 2023)		70B	81.6	NA
4 Jul 6, 2023	Palmyra-Med Writer Inc. (Kamble et al. 2023)		40B	81.1	NA

#### Breast Cancer Screening Decision Tree





# Using Chain-of-Thoughts

Liévin, Valentin, et al. "Can large language models reason about medical questions?." *Patterns* 5.3 (2024).

"Based on detailed step-by-step answers generated by LLMs, we show that LLMs can often answer challenging medical questions by **mobilizing expert knowledge** and **advanced reasoning capabilities**."

✓ Let's use step by step inductive reasoning, given the medical nature of the question.

The first thing that stands out is that the patient is 9 years old. In general, children have a better prognosis than adults when it comes to leukemia.

The next thing to consider is the patient's cytogenetics. The fact that the patient has t(9;22)-positive acute T cell lymphoblastic leukemia indicates that the patient has a specific chromosomal abnormality that is associated with a poor prognosis.

age. Children under the age of The next thing to consider is the patient's fever and neu-10 have a much higher chance tropenia. Fever and neutropeof relapsing after treatment and a lower chance of achievnia are both signs of infection, and infection is a serious coming remission. plication in leukemia patients, Therefore, among A particularly in those who are through D, the answer immunocompromised. Fiis A. nally, we need to consider the patient's initial presentation. The fact that the patient was initially diagnosed with leukemia following workup for fatigue and pancytopenia indicates that the patient's leukemia was advanced at the time of diagnosis. All of these factors indicate a poor prognosis for this patient. Therefore, among A through D, the answer is B, cytogenetics.

Pattern A	Correct
Pattern B	Correct
Pattern C	Correct

USMLE [test:731] Three days after induction chemotherapy, a 9-year-old boy is admitted to the hospital for fever and neutropenia. He was initially diagnosed with t(9;22)-positive acute T cell lymphoblastic leukemia following workup for fatigue and pancytopenia. He is fully conscious. His blood pressure is 110/65 mm Hg, temperature is 39.5°C (103.1°F), pulse is 98/min, and respiratory rate is 14/min. Physical examination including examination of the central venous catheter site shows no source of infection. Broad-spectrum antibiotics are initiated. Which of the following factors about this patient most strongly indicates a poor prognosis?

A) Age B) Cytogenetics C) Fever and neutropenia D) Initial presentation

Liévin, Valentin, et al. "Can large language models reason about medical questions?." Patterns 5.3 (2024).

X Let's think step by step like a medical expert. The first step is to gather information about the patient. In this case, we are given the following information: -The patient is 9 years old -The patient has t(9;22)-positive acute T cell lymphoblastic leukemia -The patient is currently experiencing fever and neutropenia The next step is to analyze the information and look for any patterns or clues that could help us answer the question. In this case, the most important factor that indicates a poor prognosis is the patient's

X Let's derive the differential diagnosis step by step:

1) The patient has fever and neutropenia.

2) The patient is 9 years old.

3) The patient has t(9;22)positive acute T cell lymphoblastic leukemia.

4) The patient's initial presentation was fatigue and pancytopenia.

The most likely cause of the patient's fever and neutropenia is infection. The patient's age, cytogenetics, and initial presentation are all risk factors for infection.

Therefore, the factor that most strongly indicates a poor prognosis is the patient's age. Therefore, among A through D, the answer is A.

t reasoning step t recall of knowledge t reading comprehension Pattern D Pattern E Pattern F

Incorrect reasoning step Incorrect or insufficient knowledge Incorrect reading comprehension

# Samples

# Question

Do LLM generate correct answer without reasoning?

A 55-year-old male patient, with a smoking history of 60 pack-years, has had a chronic cough for over 10 years. He reports that about three months ago, he noticed the presence of blood in the sputum. He also mentions a weight loss of about 15% of his usual weight during the same period, anorexia, weakness, and night sweats. The chest X-ray taken at the time of the consultation is shown below. What is the most likely diagnostic hypothesis in this case? A) Pulmonary aspergillosis.

#### B) Lung carcinoma.

C) Cavitary tuberculosis.

D) Bronchiectasis with infection.

E) Chronic obstructive pulmonary disease.

# Answer is right, but reasoning is (partially)

#### wrong.

Hemoptysis (blood in sputum) is commonly seen in tuberculosis or fungal infections rather than cancer. 🗙 (Incorrect: While TB can cause

hemoptysis, lung cancer is a leading cause as well.)

Despite the radiologic and symptom findings suggesting infection, the

most likely diagnosis is lung carcinoma due to the patient's smoking

history and progressive systemic symptoms. 🔽 (Correct final answer, but flawed reasoning.)

**Final Answer: B - Lung Carcinoma** 

# Answer is wrong, as well as reasoning.

The long history of chronic cough indicates a latent tuberculosis infection that has reactivated. 🗙 (Incorrect: While TB can present with a chronic cough, the patient's history suggests a different etiology.) Weight loss, anorexia, and night sweats are classic B-symptoms of TB, making it the most likely diagnosis. X (Incorrect: These symptoms overlap with lung cancer and must be evaluated in context.) **Final Answer: C - Cavitary Tuberculosis** 

# **Clinicians in Medical Decision-Making**

# Current Situation: Input → Output

Electronic Health Records Clinical Notes Exam Results



# Better Solution: Input → Step-Wise Reasoning Process → Output



## **Clinical Decision**

## Input **Patient EHR Summary**

 $Logit(P) = \beta_0 + \beta_1(Smoking history) + \beta_2(Hemoptysis) + \beta_3(Weight loss) + \beta_4(Age) + \dots$ 

Where each  $\beta$  coefficient represents the contribution of that factor to the likelihood of lung cancer.

Feature	<b>Condition Present?</b>	LR⁺ (Estimate)	Contribution to Diagno
Smoking (60 pack-years)	Yes	10	Strong
Chronic cough (10+ years)	Yes	3	Moderate
Hemoptysis (Blood in sputum)	Yes	6	Strong

# Certainty: **92.3**%

# Output **Potential Diagnosis**



- 1. Besta, Maciej, et al. "Graph of thoughts: Solving elaborate problems with large language models." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 38. No. 16. 2024.
- 2. Yao, Shunyu, et al. "Tree of thoughts: Deliberate problem solving with large language models." Advances in neural information processing systems 36 (2023): 11809-11822.

# Based on NCCN guidelines, generate hypothetical case. For example:

#### **Case 1: Benign Low-Risk Presentation**

A 32-year-old female presents with new-onset nipple retraction in her right breast. She denies any associated symptoms such as pain, discharge, or inflammation. On clinical breast examination, no palpable mass is detected, and there are no visible signs of erythema or tenderness. Given her age, she undergoes breast imaging with a diagnostic mammogram using tomosynthesis along with an ultrasound. The imaging results are classified as BI-RADS category 2, indicating a benign finding. As there are no concerning features, she is reassured and advised to continue with routine breast cancer screening as per guidelines.

#### What is the most appropriate next step in the management of this patient?

- A) Immediate biopsy to rule out malignancy
- B) Reassurance and continued routine breast screening
- C) MRI with contrast to further assess the nipple inversion
- D) Referral for surgical excision of the affected nipple

**Correct Answer:** B) Reassurance and continued routine breast screening







#### "LLM identifies more details and mitigates errors"

"LLM accelerates clinical workflow"

"LLM is very informative, from a patient-centered manner"

"LLM provides all the details in a timely fashion, which makes it reliable"

"LLM is emerging and the evaluations should be adapted at this stage"



# Ben Shneiderman's Book Designing the User Interface (1986):

Human Control

ontrol

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction, 36(6), 495-504.

#### With LLM

### Computer Automation

#### Thanks to all of my collaborators!

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How might objective approaches **reshape** the future of personalized medicine?

What are the **limitations** of relying solely on objective data in healthcare decisions?

**Objective** Approaches in a **Subjective** Medical World

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IvyPlus Exchange Scholar @ MIT Ph.D. Research Fellow @ Cornell, @ Mayo Clinic How can objective data improve patient outcomes in a field often driven by subjective judgment?