Prompt Engineering

Dr. Mozhgan Tanhapour

Assistant Professor of Medical Informatics

Urmia University of Medical Science

Outline

Introduction

- A **prompt** is the input (such as text, code, or instructions) given to an artificial intelligence model—especially a **large language model (LLM)**
- Prompt guides AI output or response.
- It acts as the “instruction” or “query” that tells the AI what to do.
- A prompt is the starting point of the interaction with an AI system.
- The quality, clarity, and structure of the prompt significantly affect the quality of the AI’s output.

Introduction (Cont.)

- **Types of Prompt:**
  - **AI learning setup:**
    - **Few-shot prompts** – Giving examples before asking for output. (can be equal to contextual prompt)
    - **Zero-shot prompts** – Asking without examples, relying on the AI’s general knowledge. (can be equal to instructional prompt)

Introduction (Cont.)

- **Prompting**
  - Prompting is the process of providing input to an AI model.
  - The quality of your output often depends on how well you're able to prompt the model.
  - Prompting is both an art and a science
- **Prompt Engineering**
  - Learn strategies, techniques, and tools to construct prompts

Rules of prompting

1. Use the latest model

- For best results, we generally recommend using the latest, most capable models.
- Newer models tend to be easier to prompt engineering.

Rules of prompting (Cont.)

2. Put instructions at the beginning of the prompt and use ## or "" to separate the instruction and context

❌ Summarize the text below as a bullet point list of the most important points:

Your text

✅ Summarize the text below as a bullet point list of the most important points:

“Your text”

Rules of prompting (Cont.)

3. Be specific, descriptive, and as detailed as possible about the desired context, outcome, length, format, style, etc.

❌ Write a poem about OpenAI.

✅ Write a short inspiring poem about OpenAI, focusing on the recent DALL-E product launch (DALL-E is a text to image ML model) in the style of a {famous poet}

Rules of prompting (Cont.)

4. Articulate the desired output format through examples

❌ Extract the entities mentioned in the text below. Extract the following 4 entity types: company names, people names, specific topics, and themes.

Your text

Rules of prompting (Cont.)

4. Articulate the desired output format through examples

Extract the important entities mentioned in the text below. First, extract all company names, then extract all people's names, then extract specific topics that fit the content, and finally extract general overarching themes

Desired format:
Company names: <comma_separated_list_of_company_names>
People names: -||-
Specific topics: -||-
General themes: -||-

Your text

Rules of prompting (Cont.)

5. Start with zero-shot, then few-shot; neither of them worked, then fine-tune

✅ Zero-shot

Extract keywords from the text below

Text: {text}

Keywords:

Rules of prompting (Cont.)

5. Start with zero-shot, then few-shot; neither of them worked, then fine-tune

Few-shot:

Extract keywords from the corresponding texts below.

Text 1: Stripe provides APIs that web developers can use to integrate payment processing into their websites and mobile applications.

Keywords 1: Stripe, payment processing, APIs, web developers, websites, mobile applications

##

Text 2: Your text

Keywords 2:

Rules of prompting (Cont.)

6. Reduce “fluffy” and imprecise descriptions.

❌ The description for this product should be fairly short, a few sentences only, and not too much more.

✅ Use a 3 to 5 sentence paragraph to describe this product.

Rules of prompting (Cont.)

7. Instead of just saying what not to do, say what to do instead.

The following is a conversation between an Agent and a Customer. DO NOT ASK USERNAME OR PASSWORD. DO NOT REPEAT.

Customer: I can’t log in to my account.

Agent:

Rules of prompting (Cont.)

7. Instead of just saying what not to do, say what to do instead.

The following is a conversation between an Agent and a Customer. The agent will attempt to diagnose the problem and suggest a solution, whilst refraining from asking any questions related to PII. Instead of asking for PII, such as username or password, refer the user to the help article www.samplewebsite.com/help/faq

Customer: I can’t log in to my account.
Agent:

Rules of prompting (Cont.)

8. Code Generation Specific - Use “leading words” to nudge the model toward a particular pattern

```
# Write a simple Python function that
# 1. Ask me for a number in miles
# 2. It converts miles to kilometers
```

Rules of prompting (Cont.)

8. Code Generation Specific - Use “leading words” to nudge the model toward a particular pattern

In this prompt below, adding “*import*” hints to the model that it should start writing in Python. (Similarly, “SELECT” is a good hint for the start of a SQL statement.)

✅

```
# Write a simple python function that
# 1. Ask me for a number in mile
# 2. It converts miles to kilometers

import
```

Rules of prompting (Cont.)

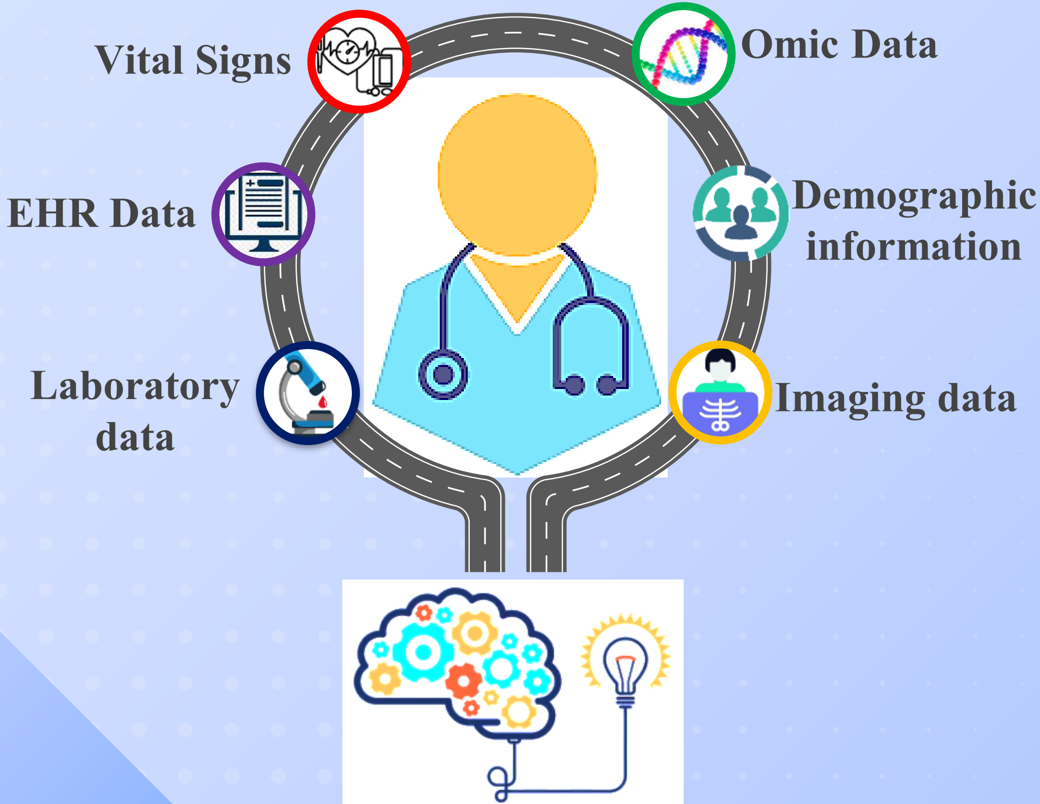
9. Use the Generate Anything feature

- Beyond text: Generating images, code, tables, charts, structured data, or even interactive elements.
- Take advantage of the model's ability to generate anything you might need — whether that's code snippets, structured documents, design drafts, or creative writing.

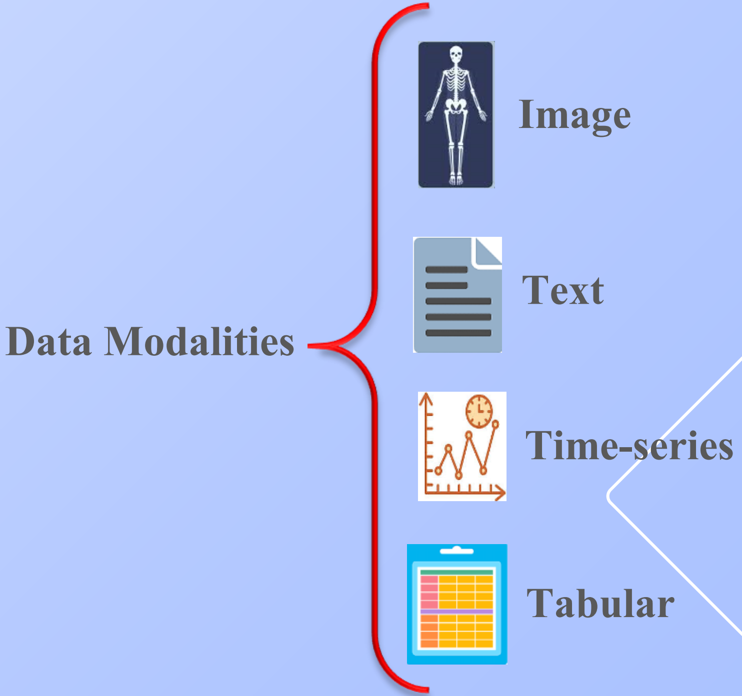
Multimodal AI models in Medical Diagnosis

Outline

Introduction

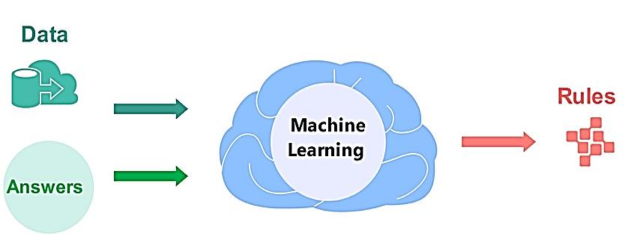


Make informed decisions and contextualize their findings



Introduction (Cont.)

Using a single data modality

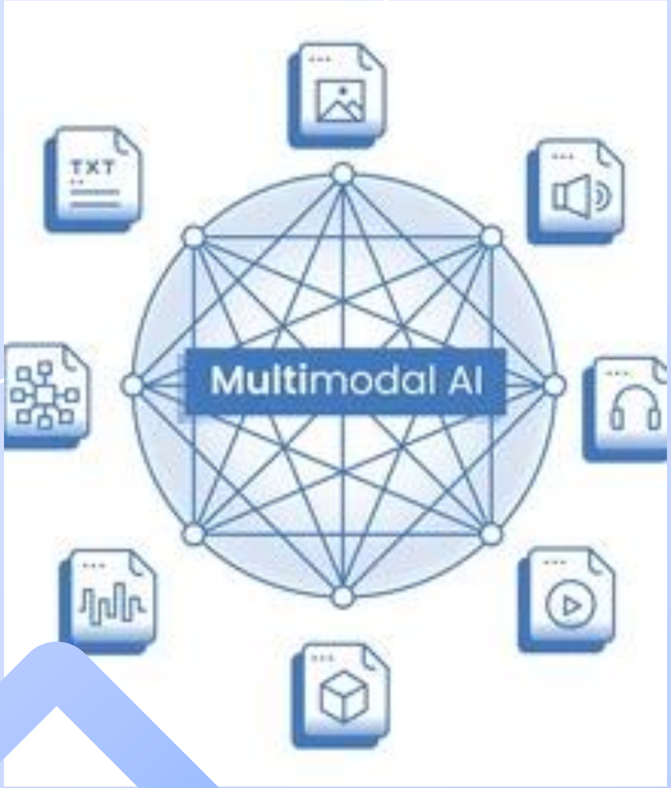


Advanced machine learning methods efficiently incorporate multimodal data to better represent clinicians' approach in real world

Limitations of traditional Machine Learning models in effectively replicating the clinical practice for decision making

Multi-Modal AI systems

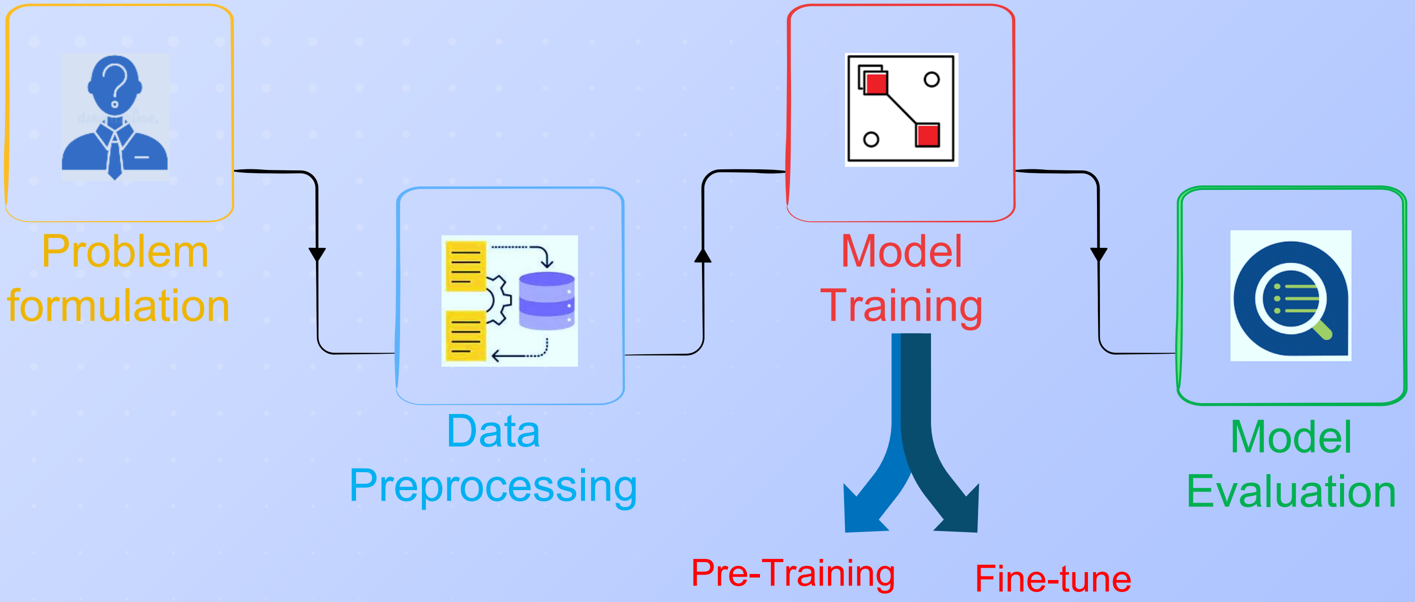
Multimodal artificial intelligence systems aim to build models that can process and relate information from multiple modalities



02

Problem solving with Multimodal AI Models

Developing a Multimodal AI Model (Cont.)



Developing a Multimodal AI Model (Cont.)

Data Pre-Processing

Prepares raw data for machine learning by improving its quality and structure, leading to better model performance and reliability.

Data Cleaning

- Missing values
- Duplicates
- Irrelevant outliers

Data Transformation

- Reformat and scale
- Data Normalization
- Vector embeddings
- Resizing Images

Data Reduction

- Feature selection
- Dimensionality reduction

Data Integration

- Merging data from multiple sources or datasets

Developing a Multimodal AI Model (Cont.)

Pre-training

Teaching a model to understand different data types, like text, images, or audio, **before** fine-tuning a specific task.

Pretext Tasks:
Learn useful representations of the data and practice problems.

How are these different types of data related?
Learning rich information about the semantic concepts

Provide a strong initialization point by training the model on large datasets

- **For images: ImageNet**
- **For Text: BookCorpus**
- **For Medical Images: MIMIC**

Developing a Multimodal AI Model (Cont.)

Fine-tuning Goals

Adjusting the model to the target task structure (e.g., for a classification problem, changing the last layer of the model)

Adjusting the model to the target task

Training the model on the target data

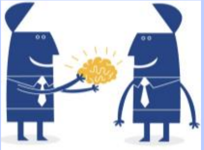
Training the model on the target data (training all weights or only weights of specific layers)

Developing a Multimodal AI Model (Cont.)

Pre-training, Fine-tuning

Training examples in
large, general datasets

Feed data to the model
initialized with random weights



Transfer: Used the learned features for a specific downstream task

Target specific dataset

Feed data to the pretrained model

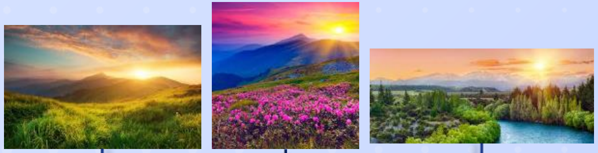
Final model

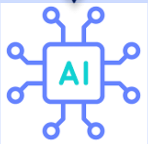
Developing a Multimodal AI Model (Cont.)

Pre-training, Fine-tuning

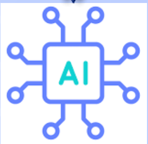
A model pre-trained on medical images is likely to outperform models pre-trained on natural images during fine-tuning (Semantic context!)

Natural images

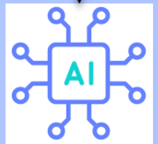




A medical domain-specific dataset (Radiology images)



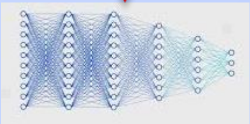
Fine-tuning with X-ray images to diagnose bone fractures



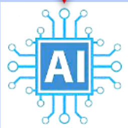
Developing a Multimodal AI Model (Cont.)

Training a multi-modal AI

Modality-specific pre-trained models



A convolutional neural network trained on chest X-ray images



A transformer model trained on EHR

Combined

Fine-tuning the multimodal (images-text) AI model

Diagnosis Pneumonia

Developing a Multimodal AI Model (Cont.)

Model Evaluation

Robusstness

The model's ability to maintain stable and accurate performance even when the input data contains noise

Interpretability

The degree to which a model's decisions can be understood and explained by humans

Generalizability

The ability of a trained model to perform effectively and accurately on new, unseen data

03

Evidences

Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment

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Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment

Kenneth A. McLean, Alessandro Sgrò, Leo R. Brown, Louis F. Buijs, Katie E. Mountain, Catherine A. Shaw, Thomas M. Drake, Riinu Pius, Stephen R. Knight, Cameron J. Fairfield, Richard J. E. Skipworth, Sotirios A. Tsaftaris, Stephen J. Wigmore, Mark A. Potter, Matt-Mouley Bouamrane, Ewen M. Harrison & TWIST Collaborators

npj Digital Medicine **8**, Article number: 121 (2025) | Cite this article

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Goal: Diagnosing **surgical site infections (SSIs)** from patient-generated data, including patient-reported outcome measures (PROMs) and wound images to support remote postoperative monitoring and reduce clinician workload

Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment (Cont.)

Population: 423 patients (1540 submission)

age ≥ 18 years

undergoing gastrointestinal surgery

Intervention:

patients given access to the online platform throughout the early postoperative period (postoperative day 1–30)

Patients submit an image of their surgical wound(s), and a series of patient-reported outcomes (PROMs)

Question	Options
1. Has the wound been painful to touch	No, Yes
2. Is there liquid coming from the wound site	No, Yes
3. Is there redness spreading away from the wound?	No, Yes
4. Has the area around the wound become swollen?	No, Yes

Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment (Cont.)

Outcomes

Qualified clinician on remote clinical triage

Suspected of SSI

Yes (Moderate- or high-risk of SSI)

No (low risk of SSI)

In-person clinician review within 48h of the response submission

Confirmed diagnosis of SSI

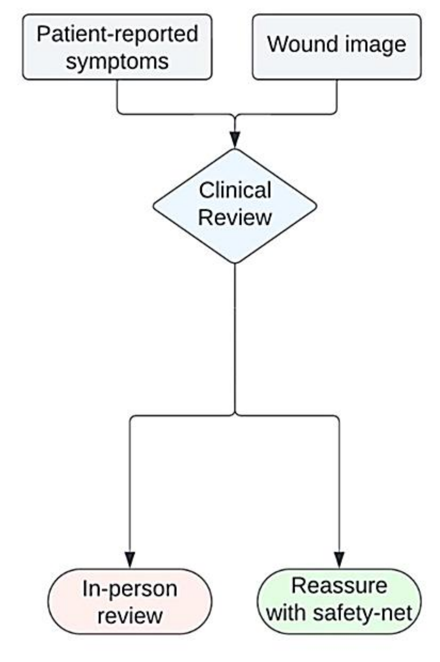
Yes (Moderate- or high-risk of SSI)

No (low risk of SSI)

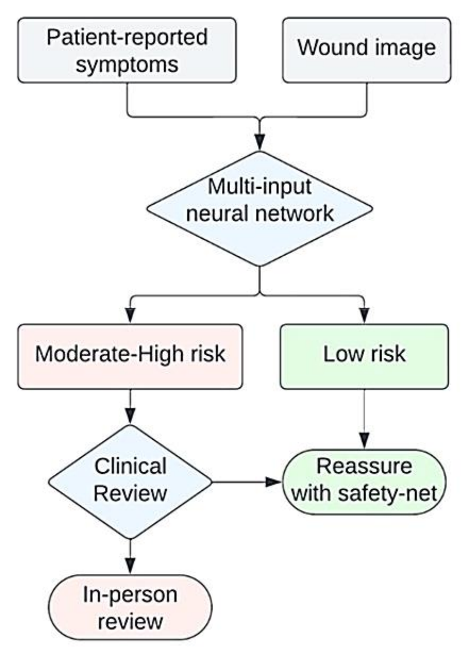
Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment (Cont.)

Considered Scenarios

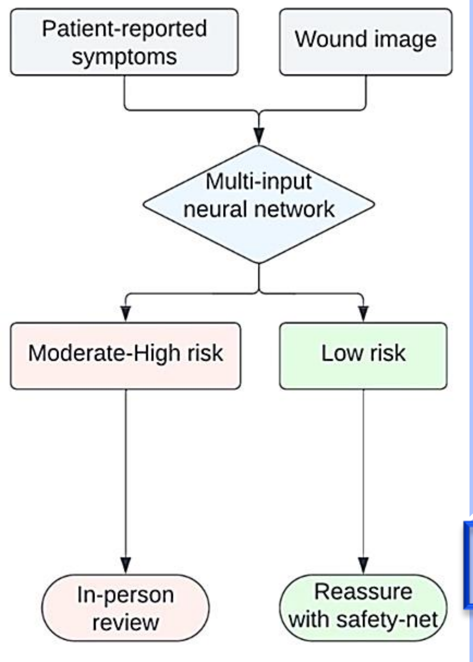
Clinical assessment



Partial automated assessment



Fully automated assessment



Multimodal machine learning to predict surgical site infection with healthcare workload impact assessment (Cont.)

Multimodal AI Model accuracy: predicts confirmed **SSI** within **48 hours,** with performance **comparable to clinician triage:**

- ❖ **Model AUC: 0.762** (95% CI: 0.690–0.835)
- ❖ **Clinician AUC: 0.777** (95% CI: 0.721–0.832)

Workload Reduction: Simulated implementation showed an **82.4% reduction in staff time for partial automated assessment**:

- ❖ From **25.8 hours** to **9.1 hours** for triaging patient submissions.

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial

Original Investigation | Gastroenterology and Hepatology

July 19, 2024

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence

A Randomized Crossover Trial

Haochen Cui, MD[1]; Yuchong Zhao, MD[1]; Si Xiong, PhD[1]; et al

Author Affiliations | Article Information

JAMA Netw Open. 2024;7(7):e2422454. doi:10.1001/jamanetworkopen.2024.22454

Goal: To advance the clinical diagnosis of solid lesions in the pancreas through developing a multimodal AI model integrating both clinical information and endoscopic ultrasonographic (EUS) images

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)

Multimodal AI model dataset:

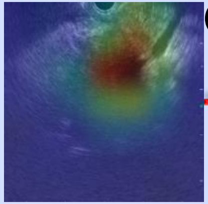
- ❖ Retrospective EUS images and clinical information of 628 patients aged ≥ 18 years with solid lesions in the pancreas
- ❖ Between 2014 and 2022, from 4 institutions across China

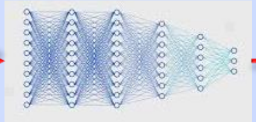
Population:

- ❖ **Prospective randomized crossover trial** with **130 patients** from January 1 to June 30, 2023

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)

Model 1: CNN
(ResNet-50) trained on EUS images

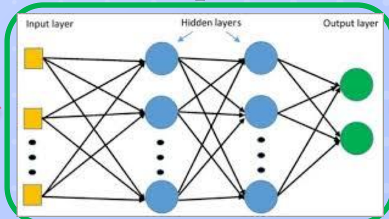




Model 2: Machine learning models
(SVM, DT, GBDT, RF) trained on
36 clinical features

Combined

Model 3: Multilayer Perceptron



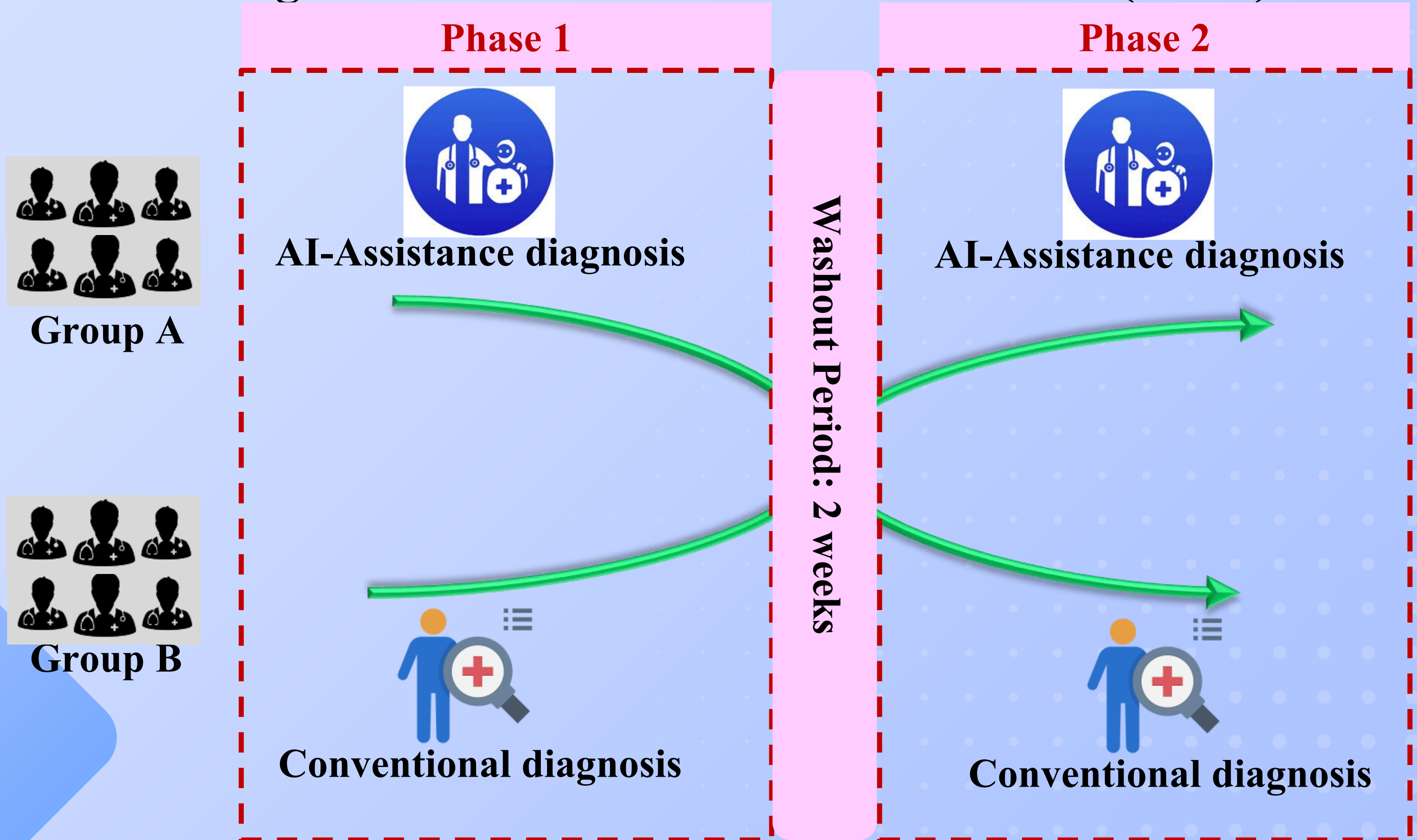
Differentiating Carcinoma and Noncancerous Lesions

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)

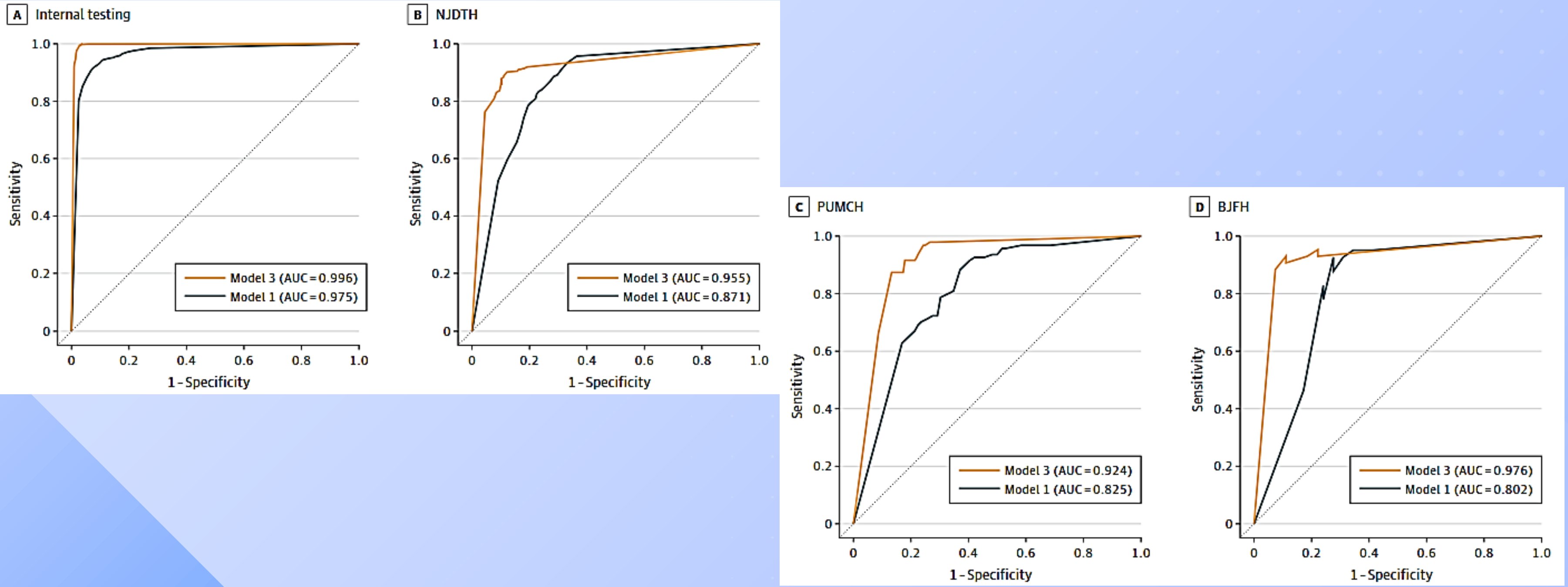
Intervention:

- Included **12 endoscopists**: 2 experts, 4 seniors, 6 novices
- **Setup**: Each endoscopist assessed the same cases **with and without AI assistance** in two sessions (separated by a 2-week washout)
- **Blinding**:
- Endoscopists were blinded to patient identities, pathology, and final diagnoses
- Random assignment was done by an **independent researcher** who was also **blinded** to the clinicians’ identities and experience levels
- **Randomization:** Endoscopists were **randomly assigned (1:1)** to two groups: with/without AI assistance

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)

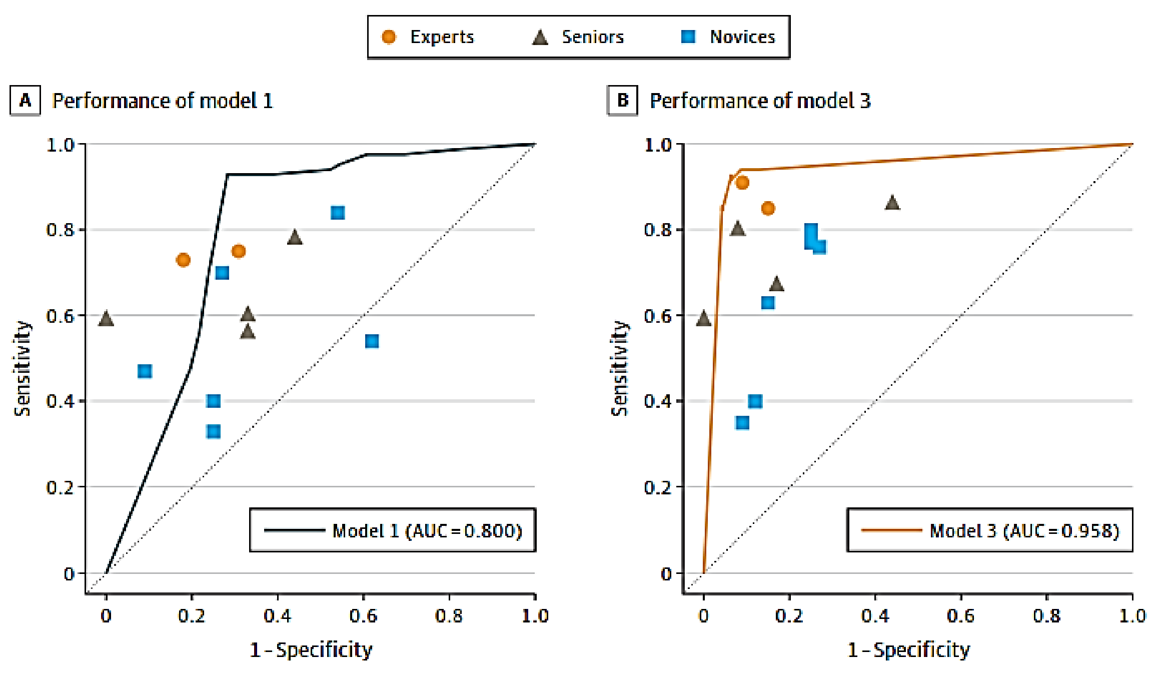


Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)



- ❖ The **area under the curve** of the **joint-AI model** ranged from 0.996 in the internal test dataset to 0.955, 0.924, and 0.976 in the three external test datasets, respectively

Diagnosing Solid Lesions in the Pancreas With Multimodal Artificial Intelligence: A Randomized Crossover Trial (Cont.)



- The **diagnostic accuracy** of **novice endoscopists** was **significantly enhanced** with AI assistance (0.69 [95% CI, 0.61-0.76] vs 0.90 [95% CI, 0.83-0.94]; *P* < .001)

04

Multimodal AI model challenges

Challenges of Multimodal AI models

Transparency

- Application of rigorous RCTs and involvement of stakeholders

Data ownership and privacy

- Implement robust data governance frameworks
- Ensure informed patient consent

Increasing inequity

Low- and middle-income countries are underrepresented in AI datasets:

- Collaborating to provide computing infrastructure for these regions

Integration into clinical workflows

- Requires alignment with existing practices
- Overcoming resistance to change among health care professionals
- Training is essential to ensure safe and effective use of AI systems

Explainable AI

Outline

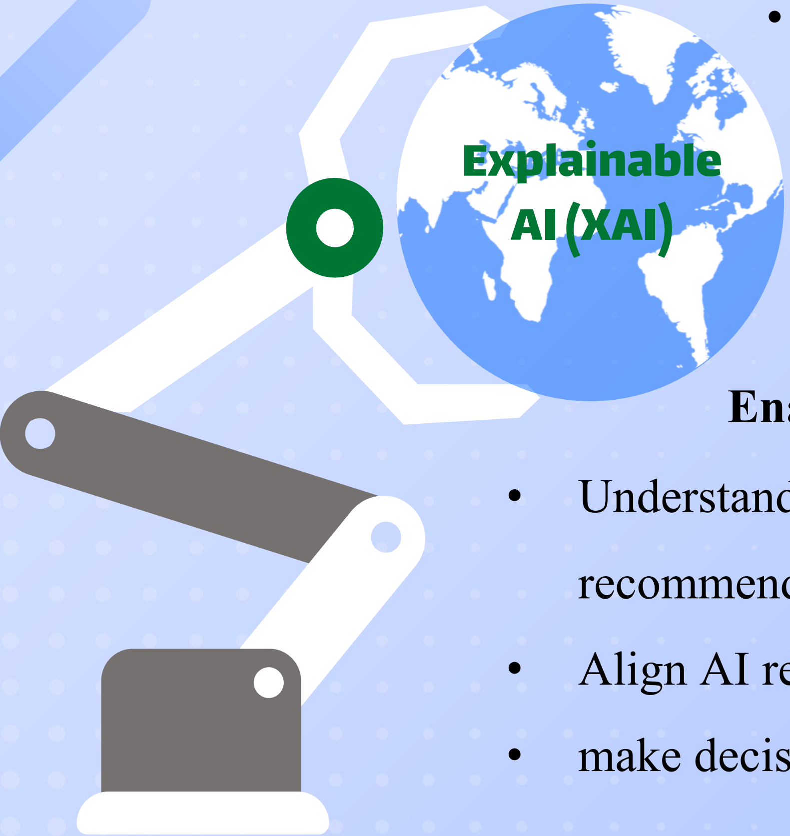
1 What is Explainability

2 Why XAI

3 Types of Explainability

4 Explainability Methods

What is Explainability?

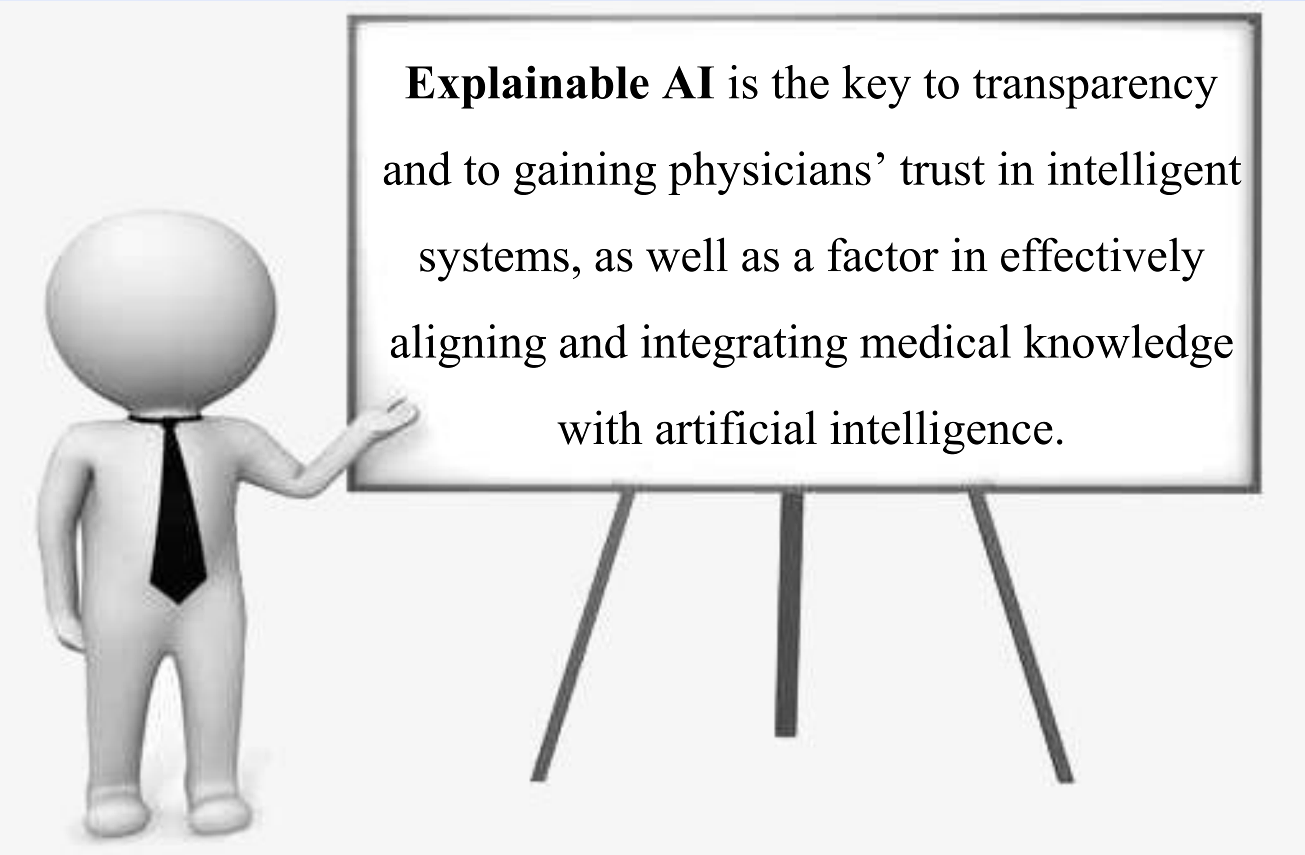


- The ability of an artificial intelligence model to provide human-understandable explanations about why certain decisions or predictions have been made.

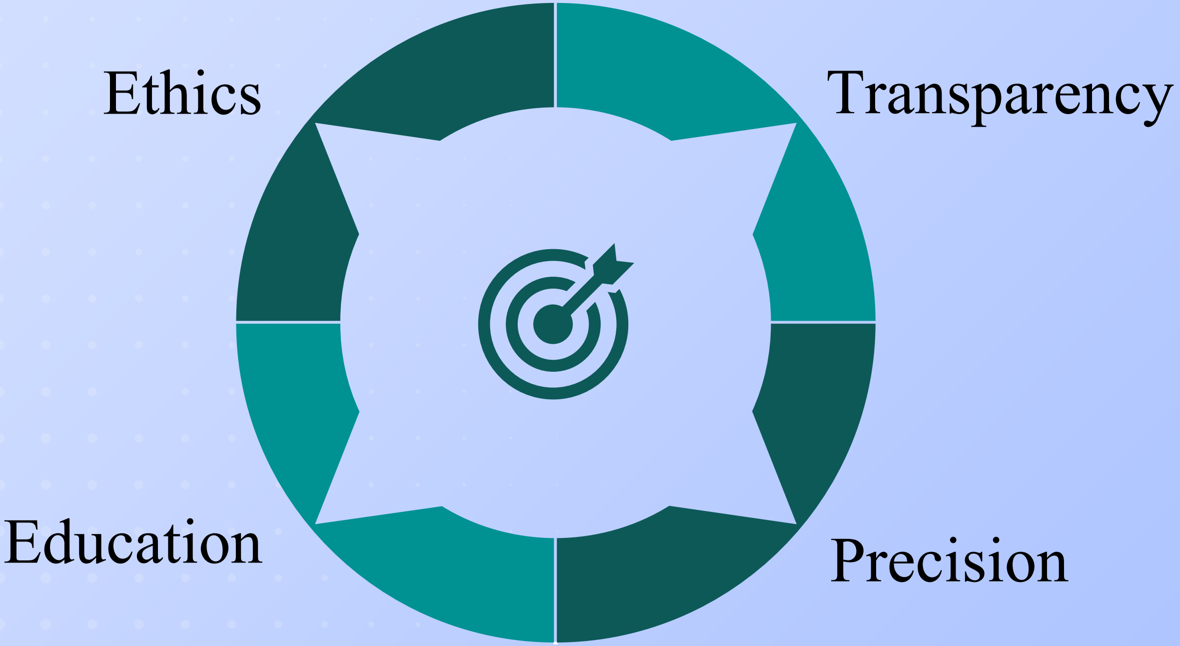
Enables a physician to:

- Understand the reasoning behind the algorithm's recommendations
- Align AI recommendations with their own clinical knowledge
- make decisions with greater confidence and accountability

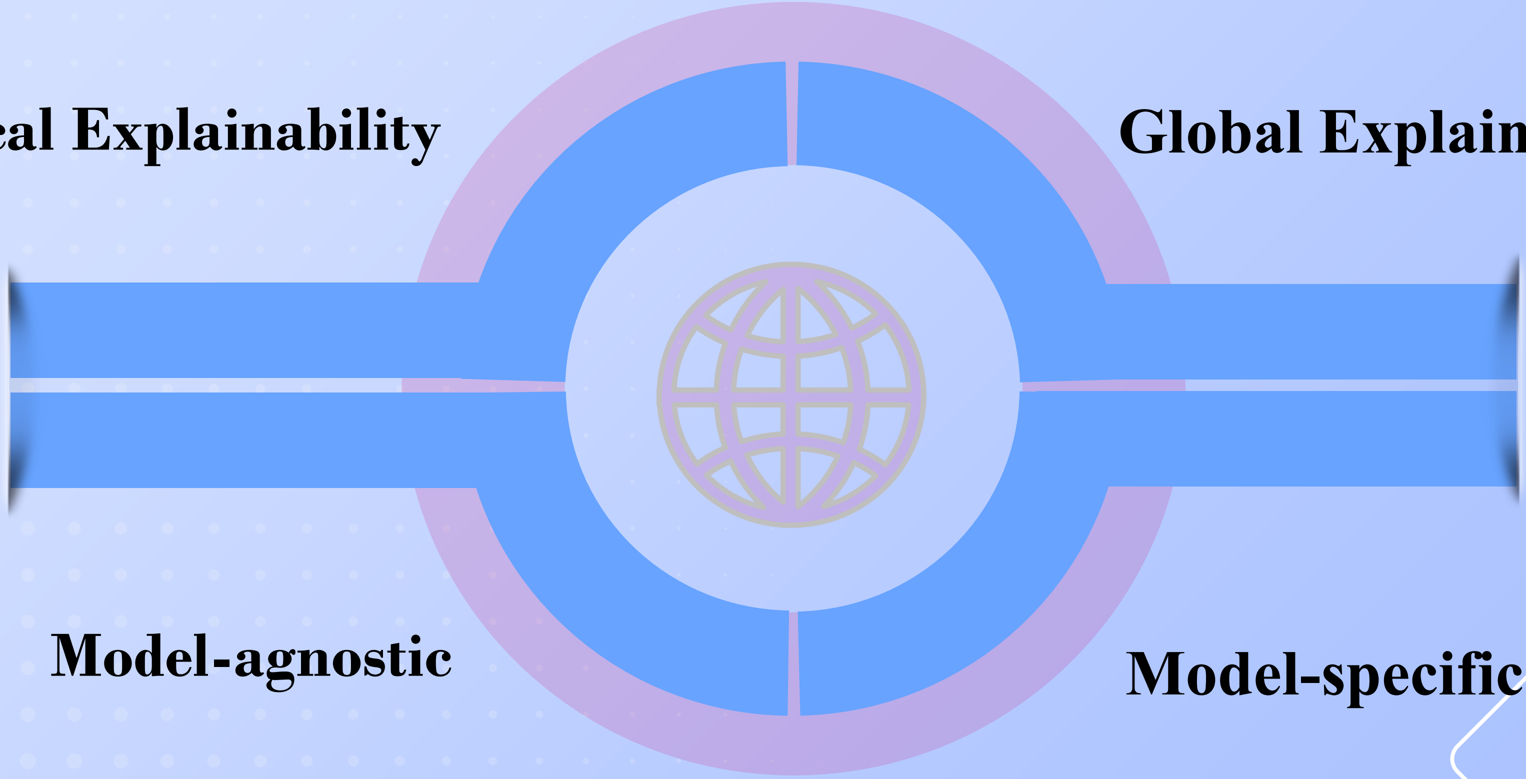
Why XAI?


Explainable AI is the key to transparency and to gaining physicians' trust in intelligent systems, as well as a factor in effectively aligning and integrating medical knowledge with artificial intelligence.

Why XAI? (Cont.)



Types of Explainability



Explainability Methods

- **Shapley Game Theory (SHAP)**
- **Model-agnostic Local Interpretable Explanations (LIME)**

Thanks

Email: Mozhgan.tanhapoor90@gmail.com