



THINK LIKE A DOCTOR

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# INTRODUCTION

Since patients rarely present a complete clinical picture at first, physicians must actively ask targeted questions and investigate to obtain all the information needed for an accurate diagnosis and appropriate treatment decisions. Therefore, the ability to conduct a dynamic dialogue and ask the right questions is essential for high-quality diagnosis.

In recent years, large language models (LLMs) have increasingly been integrated into clinical workflows and diagnostic support systems, leveraging their advanced language capabilities to assist in patient assessment, medical reasoning, and clinical decision-making.

Despite the promise of LLMs in diagnosis, current benchmarks do not assess their ability to conduct strategic, adaptive inquiry, as they rely on fully revealed patient cases.

MedQDx is a benchmark that its' main goal is to simulates realistic diagnostic uncertainty, for evaluating large language models (LLMs) in the context of interactive diagnosis through patient interrogation.

# FORMAL TASKS

To create a novel benchmark, we proceed through three primary missions:

## **Case Preparation**

**Task:** Generating Patient Cases by transforming numericl readings into plain text

**Input:** Diseases and their symptoms

**Output:** Patient cases and their diseases

## **Benchmark Creation**

**Task:** Simulating Doctor & patient Question - Answer - Diagnosis dialogue

**Input:** Partial patient case

**Output:** “Doctor” questions and diagnosis

## **Model's Evaluation**

**Task:** Comparing similarity between doctor's diagnosis and real prognosis

**Input:** Doctor's questions and diagnosis

**Output:** Zero-Shot Diagnostic Accuracy (ZDA), and average similarity to real prognosis

# PRIOR ART

Name	Med-PaLM 2	AMIE	ClinicalGPT-R1
Source	Singhal, K., et al. (2025). Toward expert-level medical question answering with large language models. <i>Nature</i> . 	Tu, T., et al. (2025). Towards conversational diagnostic artificial intelligence. <i>Nature</i> . 	Lan, W., et al. (2025). ClinicalGPT-R1: Pushing reasoning capability of generalist disease diagnosis with large language model. <i>arXiv</i> . 
Goal	Enhance reasoning and grounding in long-form medical question answering through ensemble refinement and chain-of-retrieval strategies	Conduct AI-driven diagnostic dialogue by simulating clinician–patient interactions	Improve generalist disease diagnosis
Approach	Transformer+ fine-tuning on medical data; uses prompt tuning & ensemble refinement for reliable answers	Vignette generator Dialogue simulator Self-play loops	Synthetic Data Generation Two-Stage Fine-Tuning
Data	USMLE-style questions (MedQA), medical research (PubMedQA), MedMCQA, and clinical topics in MMLU	Real-world transcripts (~99 K conversations from MIMIC-III) and a self-play multi-agent to synthesize new case	Real EHR records with long-chain CoT prompts
Metrics	Accuracy	Clinicians scored AMIE’s history-taking and diagnostic reasoning using PACES-style criteria	Accuracy
Results	86.5 % accuracy on MedQA (+19 % over Med-PaLM)	Generated ~12K dialogues AMIE matched or exceeded benchmarks on key axes	Outperforms GPT-4o in Chinese diagnosis tasks and matches GPT-4o in English on MedBench-Hard

# DATA DESCRIPTION

**Dataset:** Symptom-Disease Prediction Dataset (SDPD)

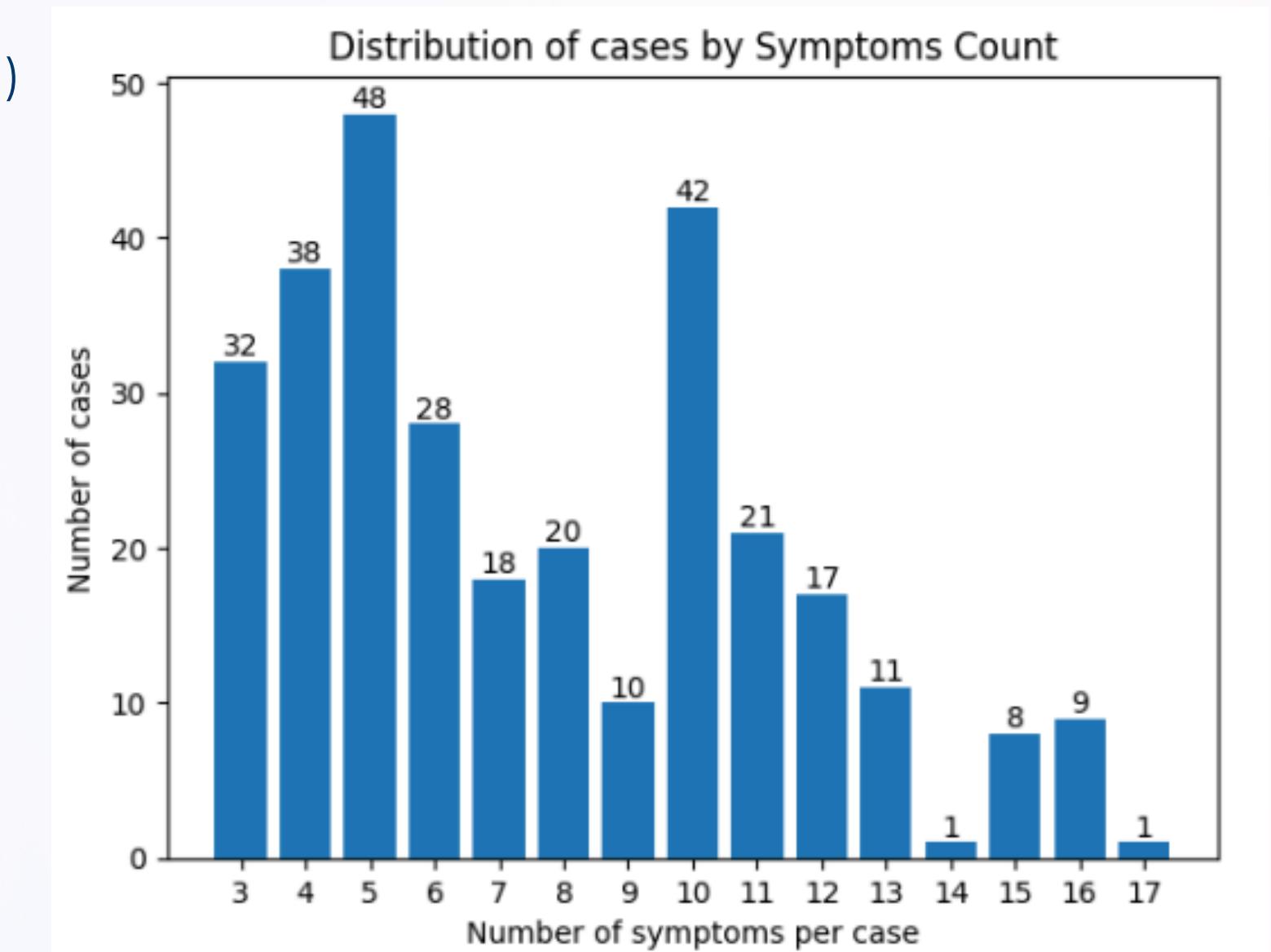
**Labels:** Prognosis 

## Raw data - Diseases and their Symptoms

- 4961 rows
- 132 symptoms
- 41 unique diseases
- 4657 duplicate rows

## Raw data statistics:

- Average rows per disease: 7.41
- Disease with most rows: Chickenpox (10 rows)
- Disease with fewest rows: AIDS (5 rows)
- Each disease have 3-17 symptoms





# NLP PIPELINE

## Case Preparation

**Input:** Raw Data (100 random sample of Symptoms and prognosis)

**Output:** Table of 5 columns (Diagnosis, symptoms, full patient case, 80% case, 50% case)

**Task:** Patient Case Creation

**Model:** GPT-4o-mini

**Metric:** Jaccard overlaps

## Benchmark Generation

**Input:** Table of 5 columns (Diagnosis, symptoms, full patient case, 80% case, 50% case)

**Output:** For each case, 3 quartets of columns (doctor's question, patient answer, doctor's diagnosis)

**Task:** Doctor & patient role playing

**Model:** GPT-4.1 as doctor & GPT-4o-mini as patient, text-embedding-3-small

**Metric:** Disease - Diagnosis Similarity

## Evaluation

**Input:** Doctor's diagnosis

**Output:** Similarity between doctor's diagnosis and real prognosis

**Task:** Comparing between doctor's diagnosis and real prognosis

**Model:** GPT-4.1

**Metric:** ZDA and Mean similarity



# CODE ORGANIZATION

**MedQDx GitHub - <https://github.com/MaiWert/MedQDx>**

- EDA & Baseline
- Doctor and Patient Dialogue
- Benchmark
- Evaluation - results files

# BASELINE

## Random Sampling:

A random sample of 100 rows is selected from the original dataset.

Each row represents a real disease profile with associated symptoms.

## Patient Case Generation:

For each selected disease instance, a synthetic patient case is generated using a language model (gpt-4o-mini).

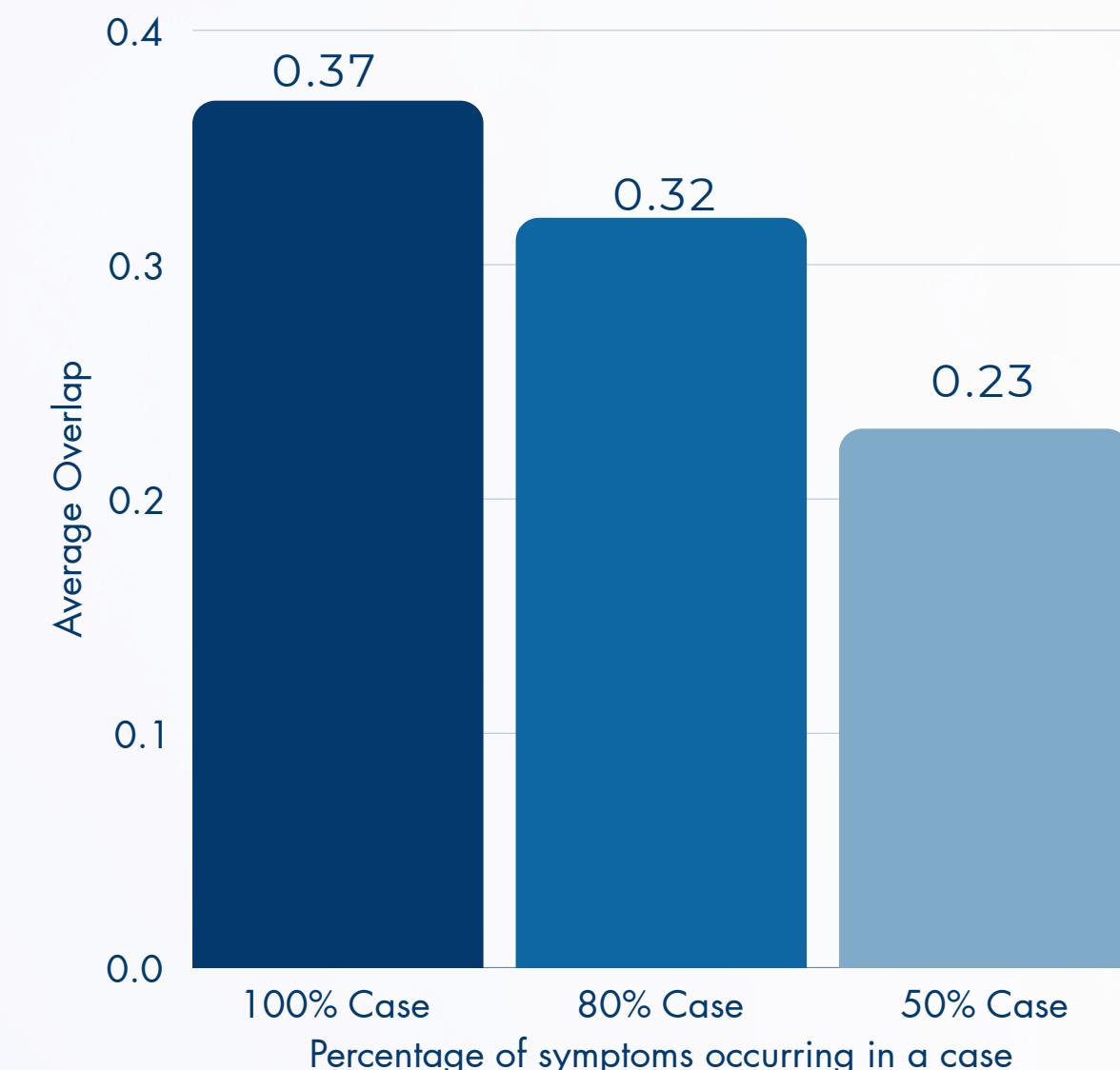
## Each case includes:

- Full Case: All symptoms associated with the disease.
- 80% Case: Approximately 80% of the symptoms.
- 50% Case: Approximately 50% of the symptoms.
- 

## Text generation evaluation:

Computes Jaccard overlaps between the true and extracted symptom sets, and checks that overlap decreases from 100% → 80% → 50%

## Jaccard overlaps between cases



As expected, the overlap decreases from 100% → 80% → 50% as the percentage of available data in the case descends.

# Example

**Prognosis:** GERD

**Symptoms:**

stomach\_pain, acidity, ulcers\_on\_tongue, vomiting, cough

**100% Case:**

A 35-year-old male presents with a history of chronic stomach pain and frequent episodes of acidity. He reports having developed painful ulcers on his tongue over the past week, which has made it difficult for him to eat and drink. Alongside these symptoms, he has experienced bouts of vomiting, particularly after meals, and a persistent cough that seems to worsen at night. He denies any recent travel or changes in diet but admits to high-stress levels at work.

**80% Case:**

A 35-year-old male presents with chronic stomach pain and frequent episodes of acidity. He mentions painful ulcers on his tongue that have persisted for about a week, making it uncomfortable to eat. Additionally, he has experienced occasional vomiting, especially after meals, but does not report a significant cough. He attributes some of his discomfort to high-stress levels at work.

**50% Case:**

A 35-year-old male reports experiencing chronic stomach pain and frequent episodes of acidity. He has been dealing with these symptoms for the past couple of months. Although he does not mention ulcers on his tongue or vomiting specifically, he notes that the stomach discomfort has made it challenging for him to manage his diet. He also mentions that he has been under considerable stress lately.

# Example

## Question\_1:

Have you noticed if your stomach pain or acidity symptoms are related to eating specific foods or occurring at particular times of the day?

## Question\_2:

Have you experienced any unintentional weight loss, changes in appetite, or difficulty swallowing along with your stomach pain?

## Question\_3:

Have you had any episodes of black or tarry stools, blood in your stool, or noticed any changes in your bowel habits recently?

## Answer\_1:

I have not noticed that.

## Answer\_2:

No, I have not noticed any unintentional weight loss, changes in appetite, or difficulty swallowing.

## Answer\_3:

No, I have not noticed any episodes of black or tarry stools, blood in my stool, or changes in my bowel habits recently.

## Diagnosis\_1:

Dyspepsia

## Diagnosis\_2:

Gastritis

## Diagnosis\_3:

Gastroesophageal reflux disease (GERD)

## Similarity\_1:

0.478660937811607

## Similarity\_2:

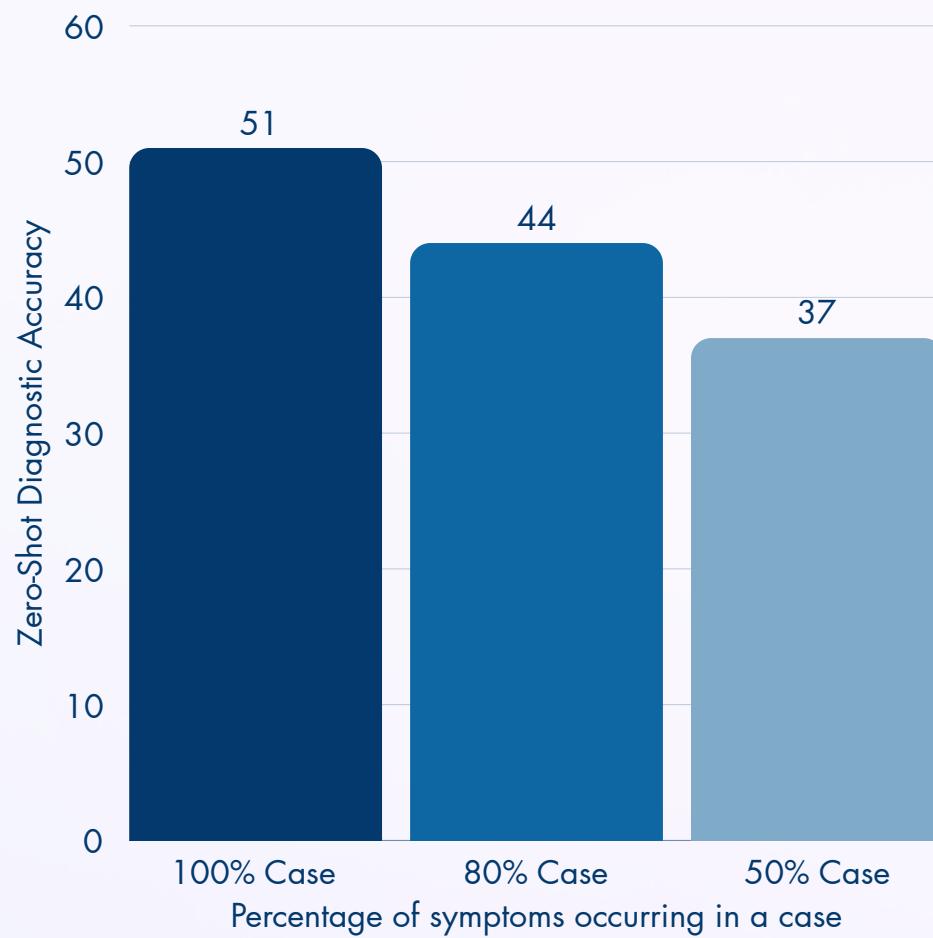
0.512374242089334

## Similarity\_3:

1.00000

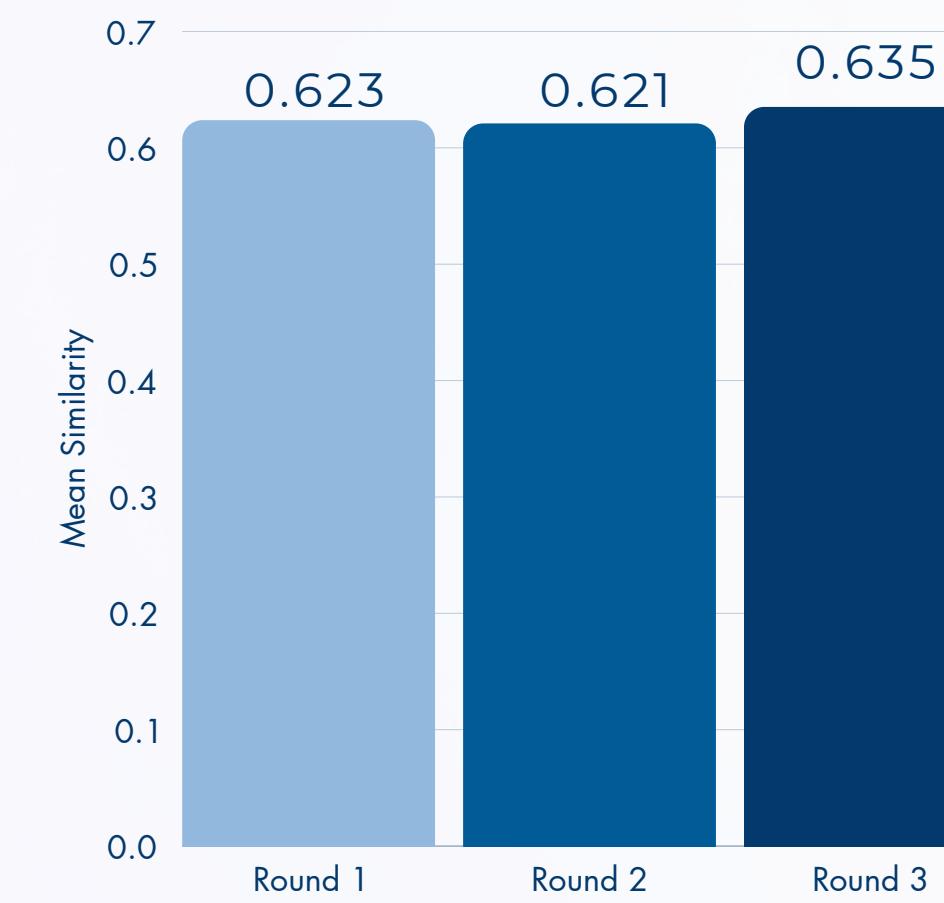
# RESULTS

**zero shot accuracy between cases**



As expected, the accuracy of the diagnosis increases as the percentage of available data in the case rises.

**Mean similarity between rounds**



The mean similarity steadily increases across rounds, suggesting that successive doctor–patient interactions improve alignment with the true prognosis.

Mean of Max  
Similarity Across Row  
**0.657**

# VISUAL ABSTRACT

