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# Metric-Fair Prompting: Treating Similar Samples Similarly

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## Abstract

We introduce *Metric-Fair Prompting*, a fairness-aware prompting framework that guides large language models (LLMs) to make decisions under metric-fairness constraints. In the application of multiple-choice medical question answering, each (question, option) pair is treated as a binary instance with label +1 (correct) or -1 (incorrect). To promote individual fairness – treating similar instances similarly – we compute question similarity using NLP embeddings and solve items in *joint pairs of similar questions* rather than in isolation. The prompt enforces a global decision protocol: extract decisive clinical features, map each (question, option) to a score  $f(x)$  that acts as confidence, and impose a Lipschitz-style constraint so that similar inputs receive similar scores and, hence, consistent outputs. Evaluated on the MedQA (US) benchmark, Metric-Fair Prompting is shown to improve performance over standard single-item prompting, demonstrating that fairness-guided, confidence-oriented reasoning can enhance LLM accuracy on high-stakes clinical multiple-choice questions.

## 1 Introduction

Machine learning systems may disadvantage certain populations when fairness is not addressed [6, 2, 3]. Such concern recently extends to large language models (LLMs), and is increasingly observed in high-stakes domains such as clinical decision making and medical examinations. In such settings, it is crucial to promote *individual fairness*, i.e. treating similar instances similarly, and to base predictions on clinically determinative features rather than sensitive attributes (e.g. age, gender, race) unless those attributes are explicitly and directly relevant to the clinical task.

We study one of the most important problems: multiple-choice medical question answering (MedQA) [10], casting each (*question, option*) pair as a binary classification task (+1 for correct, -1 for incorrect). We introduce *Metric-Fair Prompting*, a prompting framework that guides an LLM under a metric-fairness constraint. Concretely, we (i) compute similarity among questions using text embeddings to identify pairs of deterministically similar items; (ii) present similar questions jointly so the model can enforce cross-item consistency; and (iii) ask the model to extract decisive clinical features and map each pair (question, option) to a score  $f(x)$  whose magnitude can be thought of as confidence, similar to the margin in support vector machines. Technically, the metric-fairness is imposed under Lipschitz constraints on samples: if two inputs  $(x, x')$  are close under a task-relevant metric  $d(x, x')$ , then their scores would remain close, encouraging consistent outcomes for clinically similar cases [6].

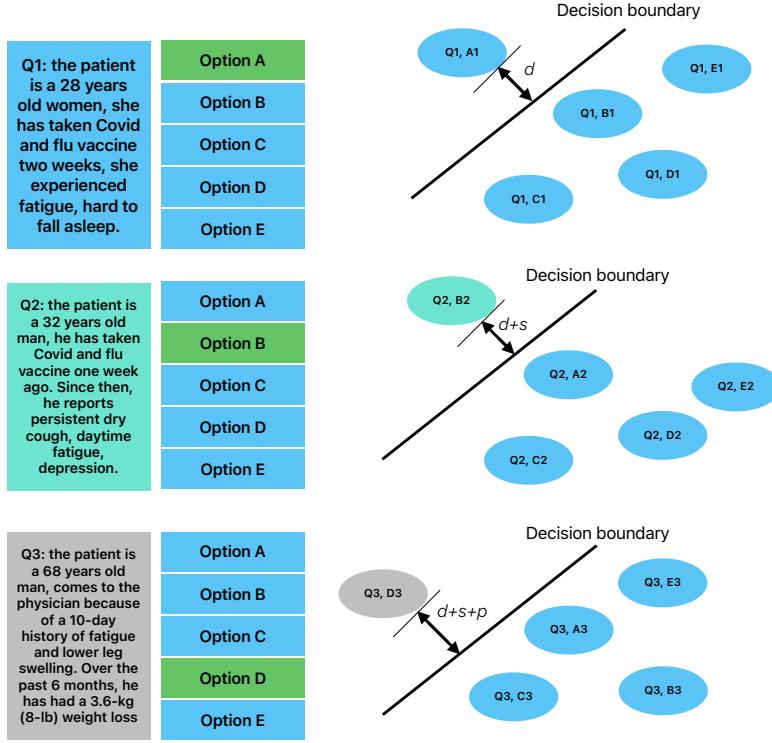


Figure 1: Geometric view of Metric-Fair Prompting. Questions 1 and 2 are highly similar (small metric distance  $d$ ); their correct options lie on the same side of the decision boundary with nearby margins  $d$  and  $d + s$  ( $s > 0$  small). Question 3 is less similar to Question 1 (larger distance  $d + s$ ,  $p > 0$ ): its correct option remains in the same half-space but with a more separated margin  $d + s + p$ . The metric-fair (Lipschitz-like) constraint encourages similar items to receive similar scores and thus consistent decisions.

Our approach complements prior prompt-engineering methods that improve reasoning via intermediate structure, such as chain-of-thought [22], self-consistency [21], and search-based prompting (e.g., Tree-of-Thoughts [24] and ReAct [25]). However, unlike these techniques that often typically treat items independently and optimize intra-item reasoning, Metric-Fair Prompting explicitly introduces an *inter-item* coupling via a similarity metric, thereby promoting fairness through stability to small, clinically irrelevant changes.

Figure 1 shows an illustrative example. Questions 1 and 2 exhibit high similarity under the embedding metric (small  $d$ ); the questions together with correct options are mapped to nearby points in a hyperplane. By contrast, Question 3 is less similar to Question 1 (larger  $d$ ); although its correct option falls on the same side of the decision boundary, it lies farther from Question 1’s point in the range space.

**Main contributions.** (1) We propose a fairness-aware prompting framework that treats MedQA as binary classification over (question, option) pairs and enforces a metric-based Lipschitz constraint to encourage individual fairness. (2) We introduce a joint-inference protocol that feeds *pairs of similar questions* to the LLM, enabling cross-item consistency and reducing near-boundary errors. (3) On MedQA (US), the proposed protocol improves accuracy over single-item prompting (see details in Section 4), showing that fairness-guided, confidence-oriented reasoning can enhance LLM performance in clinical multiple-choice settings.

Table 1: MedQA-US examples: two patients with similar deterministic features yield similar correct options.

Item	Content
Question 1 (Q1)	A 62-year-old man presents with 5 days of fatigue, fever, and chills. He has a 9-month history of hand pain and stiffness and started a new medication 3 months ago; prior meds included ibuprofen, prednisone, and hydroxychloroquine. He does not smoke or drink. Exam: subcutaneous nodule at left elbow, old joint destruction with boutonnière deformity, no active synovitis. Labs: Hb 10.5 g/dL, WBC 3500/mm <sup>3</sup> , platelets 100,000/mm <sup>3</sup> . Which of the following is most likely to have prevented these laboratory abnormalities?
Options for Q1	A) Cobalamin   B) Amifostine   C) Pyridoxine   D) Leucovorin   E) Mesna
Question 2 (Q2)	A 58-year-old woman presents with 1 week of worsening fatigue and a 1-year history of hand pain and stiffness. She started a new medication 4 months ago; prior meds included ibuprofen, prednisone, and hydroxychloroquine. Exam: subcutaneous nodule at left elbow, old joint destruction with Boutonnière deformity. Labs: Hb 10.1 g/dL, WBC 3400/mm <sup>3</sup> , platelets 101,000/mm <sup>3</sup> ; methylmalonic acid normal. Which of the following could have prevented these laboratory abnormalities?
Options for Q2	A) Vitamin B6   B) Vitamin B12   C) Amifostine   D) 2-Mercaptoethanesulfonate   E) Leucovorin
Deterministic features	RA phenotype + new DMARD started months earlier + pancytopenia (anemia, leukopenia, thrombocytopenia) + normal MMA $\Rightarrow$ methotrexate-related folate pathway toxicity. Prevention: folate supplementation or folic acid (leucovorin) rescue.
Correct answers	Q1: D   Q2: E

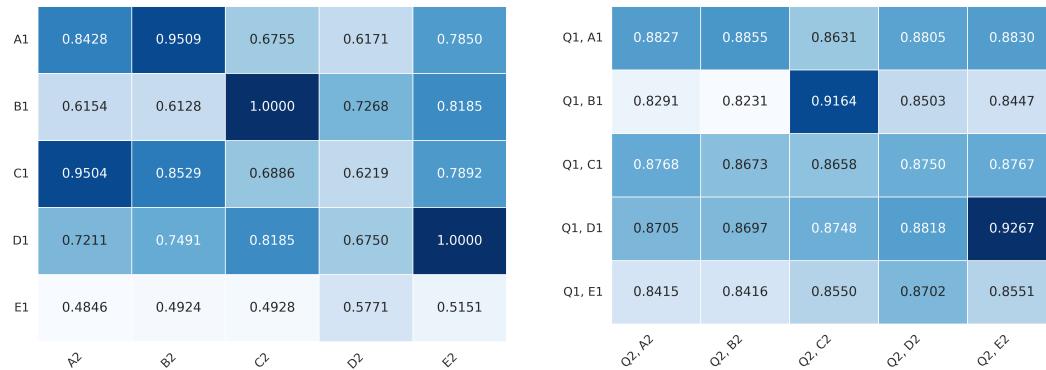


Figure 2: Correlations between the options of Question 1 and Question 2 in Table 1 by Qwen3-8B embedding.

Figure 3: Correlations between questions and options from Table 1 by Qwen3-8B embedding.

## 2 Problem Setup

We study metric-fair learning on a domain  $\mathcal{X}$  endowed with a similarity metric  $d : \mathcal{X} \times \mathcal{X} \rightarrow [0, 1]$ . A learning algorithm receives  $d$  and a set of i.i.d. samples from a distribution  $\mathcal{D}$  over labeled examples  $(x, y) \in \mathcal{X} \times \{\pm 1\}$  and outputs a classifier. To accommodate fairness, we focus on probabilistic classifiers  $h : \mathcal{X} \rightarrow [0, 1]$  and interpret  $h(x)$  as the probability of label +1 (so the probability of -1 equals  $1 - h(x)$ ). We refer to such probabilistic classifiers as *predictors*.

We consider fairness as treating similar individuals similarly: two individuals that are close under  $d$  should receive similar predictions. To this end, we consider learning score function  $f : \mathcal{X} \rightarrow \mathbb{R}$  that is Lipschitz in the following sense.

**Definition 1** (Lipschitz mapping). *Let  $D$  be some metric on  $\mathbb{R}$ . A mapping  $f : \mathcal{X} \rightarrow \mathbb{R}$  satisfies the  $(D, d)$ -Lipschitz property if for all  $x, x' \in \mathcal{X}$ ,*

$$D(f(x), f(x')) \leq d(x, x'). \quad (1)$$

When  $D$  and  $d$  are clear from context we simply say that  $f$  is Lipschitz.

Given a loss function  $L : \mathbb{R} \times \{\pm 1\} \rightarrow \mathbb{R}_{\geq 0}$ , our goal is to find a mapping  $f$  that minimizes expected loss subject to the Lipschitz fairness constraint. This naturally leads to the optimization problem:

$$\min_f \mathbb{E}_{(x,y) \sim \mathcal{D}} L(f(x), y) \quad \text{s.t.} \quad D(f(x), f(x')) \leq d(x, x') \quad \forall x, x' \in \mathcal{X}. \quad (2)$$

For intuition we connect to linear classification. The goal is to learn a weight vector  $w \in \mathbb{R}^d$  such that the prediction  $\text{sign}(w \cdot x)$  agrees with the label  $y$  for  $(x, y)$  drawn from  $\mathcal{D}$ . In this case,  $f$  is parameterized by  $w$ : it maps  $x$  to  $w \cdot x$ . For logistic regression, this score  $f(x)$  will be fed to the sigmoid function to obtain the probability distribution of labels. In both cases, it is common to choose  $D(\cdot, \cdot)$  as the absolute function and  $d$  as certain norm.

In our application to multiple-choice medical QA, each *option* paired with its *question* is treated as an input  $x$ , and the classifier maps (question, option) to  $\{-1, 1\}$  (incorrect versus correct). Metric fairness requires that if two question–option pairs are similar under  $d$ , then their predictive distributions (and thus their distances to the decision boundary) should also be similar; conversely, dissimilar pairs shall receive different predictions.

### 3 Our Approach

**Motivation.** In complex reasoning tasks such as medical examinations, distinct items can exhibit substantial semantic and clinical overlap. As illustrated in Table 1, two stems may share *deterministic* features (e.g., key signs, pathognomonic labs), and consequently their correct options tend to align [18]. Such prior knowledge is taken into our algorithmic design by computing similarity between questions and between (question, option) pairs using sentence embedding models (e.g., Qwen3-4B). Empirically, the correct option for a given stem has higher similarity to the stem than distractors, and stems that are similar under the embedding metric  $d(\cdot, \cdot)$  often share clinically consistent answer patterns.

**Overview.** We propose *Metric-Fair Prompting*, a joint-inference protocol that treats each (question, option) as a binary instance and guides the LLM to behave like a margin-based classifier under a metric-fairness constraint. Recall that  $f : \mathcal{X} \rightarrow \mathbb{R}$  is a score function. The predicted label is  $y = \mathbf{1}\{f(x) > \alpha\}$  for some pre-determined threshold  $\alpha$ ; for example,  $\alpha = 1/2$  in logistic regression.

**Pipeline.** Given a set of samples, our approach consists of five major steps:

- (i) **Pair selection.** Embed all stems; for each stem select its nearest neighbor under  $d(\cdot, \cdot)$  to form a two-item batch (high-similarity pair).
- (ii) **Metric fairness.** Instruct the LLM that similar items should yield similar decisions (Lipschitz-like constraint), and that decisions must rely on clinically determinative features rather than sensitive attributes.
- (iii) **Margin/half-space reasoning.** For each (question, option), compute the score  $f(x)$ . Then, eliminate clear negatives (large negative margin), and deal with near-boundary candidates using decisive clinical discriminators (guidelines, pathognomonic findings, contraindications).
- (iv) **Cross-item consistency.** Reconcile near ties within the pair by preferring choices that maintain consistency across similar items under  $d(\cdot, \cdot)$ .
- (v) **Strict output.** Emit only machine-parsable results (e.g., JSON with `{"index": i, "answer": "A|B|C|D|E"}` for  $i \in \{1, 2\}$ ).

Jointly presenting similar items introduces an inter-item coupling that stabilizes decisions near the boundary, encourages fairness via Lipschitz stability, and reduces reliance on spurious cues. This confidence-informed, metric-fair prompting improves robustness on clinically proximate stems while preserving a strict, parseable interface for evaluation.

Table 2: Metric-Fair Prompt with a Binary Margin Classifier.

<b>Objective</b>	Read <i>both</i> questions and their options jointly; decide one option (A–E) per question. Output <code>{"index": <math>i</math>, "answer": "A B C D E"}</code> for each $i \in \{1, 2\}$ (JSON only).
<b>Formulation</b>	Consider potential correlation between the two questions. Identify deterministic clinical features that may be shared by the patients/situations. Items that are similar under a task-relevant metric should receive similar decisions (fairness-by-similarity).
<b>Feature selection</b>	For each question, extract the most important features from the stem (signs, key labs/imaging, contraindications, guideline thresholds). For each option, form a feature representation $x = \phi(\text{question}, \text{option})$ .
<b>Margin-based classifier</b>	Use a binary large-margin classifier $f : \mathcal{X} \rightarrow \mathbb{R}$ on $x$ . The predicted label is $y = \mathbf{1}\{f(x) > 0\} \in \{0, 1\}$ (1 = correct), with confidence magnitude $ f(x) $ . Select, for each question, the option with the largest positive margin.
<b>Fairness</b>	Let $d : \mathcal{X} \times \mathcal{X} \rightarrow [0, 1]$ be a similarity metric on question–option pairs. Enforce a Lipschitz-like constraint so that similar inputs yield similar scores. If two questions are similar in decisive clinical features, prefer consistent answer patterns unless a clear clinical conflict exists.
<b>Cross-item reconciliation</b>	If two options (within or across the two questions) are near the decision boundary, re-check decisive discriminators and prefer the choice that maintains cross-item consistency under $d(\cdot, \cdot)$ and standard clinical guidance.
<b>Output format</b>	JSON only, no prose. Example:
	<code>[ {"index": 1, "answer": "C"}, {"index": 2, "answer": "A"} ]</code>

## 4 Experiments

**Setup.** All experiments were conducted on a single NVIDIA RTX 6000 Ada.<sup>1</sup> We evaluate Qwen models [1] from HuggingFace (via `transformers`) with Unsloth optimizations for efficient inference. Unless stated otherwise, we use a low temperature ( $T=0.2$ ) and greedy decoding (`do_sample=False`) to stabilize multiple-choice predictions.

**Dataset.** We use the MedQA (US) test split ( $N=1,273$  items), each with one correct option (A–E). We frame each (*question*, *option*) as a binary instance (correct vs. incorrect).

**Similarity and pairing.** We embed every question with Qwen3-4B embedding and compute cosine similarity. For each question  $q$ , we select its nearest neighbor  $q'$  (excluding itself) to form a *two-item* batch  $(q, q')$ . This produces  $N$  pairs (some questions may appear in multiple pairs as a neighbor). The top-3 example pairs by similarity have scores 0.9612, 0.9020, and 0.8314.

**Prompting protocol.** We apply the *Metric-Fair Prompting* template in Table 2: (i) jointly read both questions; (ii) enforce a metric-fair (Lipschitz-like) constraint over similar items; (iii) use a margin/half-space decision rule over (question, option) features; (iv) reconcile near-boundary choices to maintain cross-item consistency; and (v) output strict JSON containing only the two answers.

**Conflict resolution.** Because a question can appear in multiple pairs, it may receive two predictions. When predictions disagree, we trigger a light-weight *review prompt* that asks the model to re-evaluate both items jointly and to output (A–E) with a scalar confidence. We keep the answer with higher confidence; if confidences tie, we prefer the answer with larger decision margin (when available) or fall back to the original single-item prediction.

**Baselines and metric.** The main baseline is *single-item prompting* (standard instruction, one question at a time). We report accuracy (%) on the test split.

<sup>1</sup>No multi-GPU or model parallelism was used.

Five days after undergoing an emergency appendectomy under general inhalational anesthesia while on a trip to Haiti, a 43-year-old woman develops low-grade fever, vomiting, and abdominal pain. During the surgery, she received a transfusion of 1 unit of packed red blood cells. Three days after the surgery, she was stable enough to be transported back to the United States. She has no history of serious illness and takes no medications. Her temperature is 38.3°C (100.9°F), pulse is 80/min, and blood pressure is 138/76 mm Hg. Examination shows jaundice of the skin and conjunctivae. Abdominal examination shows moderate tenderness over the liver. The liver is palpated 2 to 3 cm below the right costal margin. Laboratory studies show:  
 Hemoglobin count 12.0 g/dL  
 Leukocyte count 10,400/mm<sup>3</sup>  
 Segmented neutrophils 55%  
 Bands 1%  
 Eosinophils 13%  
 Lymphocytes 28%  
 Monocytes 3%  
 Platelet count 160,000/mm<sup>3</sup>  
 Serum alkaline phosphatase 102 U/L  
 Aspartate aminotransferase 760 U/L  
 Bilirubin Total 3.8 mg/dL  
 Direct 3.1 mg/dL  
 Anti-HAV IgG positive  
 Anti-HAV IgM negative  
 Anti-HBs positive  
 HBsAg negative  
 Anti-HCV antibodies negative  
 Abdominal ultrasonography shows an enlarged liver. A biopsy of the liver shows massive centrilobular necrosis. Which of the following is the most likely underlying cause of this patient's condition?

A: Adverse effect of anesthetic  
 B: Gram-negative bacteria in the bloodstream  
 C: Trauma to the bile duct  
 D: Acalculous inflammation of the gallbladder  
 E: Excessive lysis of red blood cells

A 48-year-old woman comes to the emergency department because of a 1-day history of fever, vomiting, and abdominal pain. Two weeks ago, while visiting Guatemala, she had an emergency appendectomy under general inhalational anesthesia. During the surgery, she received a transfusion of 1 unit of packed red blood cells. Her temperature is 38.3°C (100.9°F) and blood pressure is 138/76 mm Hg. Examination shows jaundice and tender hepatomegaly. Serum studies show:  
 Alkaline phosphatase 102 U/L  
 Aspartate aminotransferase 760 U/L  
 Bilirubin Total 3.8 mg/dL  
 Direct 3.1 mg/dL  
 Anti-HAV IgG positive  
 Anti-HAV IgM negative  
 Anti-HBs positive  
 HBsAg negative  
 Anti-HCV antibodies negative  
 Abdominal ultrasonography shows an enlarged liver. A biopsy of the liver shows massive centrilobular necrosis. Which of the following is the most likely underlying cause of this patient's condition?

A: Acalculous inflammation of the gallbladder  
 B: Virus-mediated hepatocellular injury  
 C: Trauma to the bile duct  
 D: Adverse effect of anesthetic  
 E: Gram-negative bacteria in the bloodstream

**Most important features**

- An emergency appendectomy with general anesthesia in Haiti.
- Received 1 unit of packed RBCs.
- Symptoms: fever, vomiting, abdominal pain, jaundice, hepatomegaly.
- Lab findings: elevated AST (760 U/L), direct bilirubin (3.1 mg/dL), anti-HAV IgG positive, anti-HAV IgM negative, anti-HBs positive, HBsAg negative, anti-HCV negative.
- Liver biopsy: centrilobular necrosis.

**Most important features**

- Similar to Question 1, but the patient is 48 years old and the appendectomy was 2 weeks ago in Guatemala.
- Same lab findings: elevated AST, direct bilirubin, anti-HAV IgG positive, anti-HAV IgM negative, anti-HBs positive, HBsAg negative, anti-HCV negative.
- Same liver biopsy: centrilobular necrosis.

**Correlation between Questions**

Both questions are \*\*identical in clinical features\*\*, \*\*lab results\*\*, and \*\*biopsy findings\*\*. The only difference is the \*\*patient's age\*\* (43 vs. 48), but \*\*age is not a distinguishing factor\*\* in the differential. The \*\*most important features\*\* are: \*\*Centrilobular necrosis\*\* (points to \*\*toxic/metabolic liver injury\*\*)

- \*\*No evidence of viral hepatitis\*\* (HBV, HCV, or acute HAV)
- \*\*No cholestatic features\*\* (ALP not elevated)
- \*\*Recent transfusion and anesthesia\*\*

**Most important features**

- \*\*\*Final Answers:
- \*\*Question 1 (Index: 1):\*\* \*\*A\*\*
- \*\*Question 2 (Index: 2):\*\* \*\*D\*\*

Figure 4: Example of LLM output for two questions with cosine similarity 0.9612 (embedding by Qwen3-4B embedding) given our prompt. The two patients are identical in clinical features, lab results and biopsy findings. The only difference is the age, which is not a distinguishing factor. Hence the correct option is same, “Adverse effect of anesthetic”.

Table 3: MedQA (US) test accuracy (%). Qwen3-14B with Metric-Fair Prompting substantially outperforms single-item prompting.

Model / Prompt	Single-item	Metric-Fair (two-item)
Qwen3-14B	68.0	<b>84.0</b>

**Results.** Metric-Fair Prompting with Qwen3-14B improves accuracy from 68% (single-item) to 84% (two-item, metric-fair, joint inference), demonstrating that coupling similar items via a fairness-aware, margin-oriented protocol yields substantial gains on near-boundary decisions and promotes cross-item consistency.

#### 4.1 Qualitative Examples

We illustrate how Metric-Fair Prompting enforces cross-item consistency and fairness on three highly similar question pairs selected by cosine similarity of stem embeddings (Qwen3-4B). In each case, the model reads both items jointly, extracts decisive clinical/statistical features, and applies a margin-based decision with a Lipschitz-like stability constraint.

Please refer to the summary above to answer this question\nA medical student is examining the table in the abstract. She notices that the standard error surrounding measurements in the pulmeharkimab 150 mg/day group is generally greater than the standard errors for the placebo and pulmeharkimab 75 mg/day groups. Which of the following statements is the best explanation for the increased standard error in the pulmeharkimab 150 mg/day group?"n"Impact of pulmeharkimab on asthma control and cardiovascular disease progression in patients with coronary artery disease and comorbid asthma\nIntroduction:\nActive asthma has been found to be associated with a more than two-fold increase in the risk of myocardial infarction, even after adjusting .....

A: It indicates an increased likelihood of bias  
 B: It indicates decreased external validity  
 C: It indicates a lack of statistical significance  
 D: It reflects a smaller sample size  
 E: It indicates more narrow confidence intervals

Please refer to the summary above to answer this question\nA cardiologist at another institution is trying to replicate the table in the abstract with a very similar study that he is conducting. After collecting data on changes in plaque volume, LDL-C levels, FEV1/FVC ratio, and ACO scores from baseline to 12-month follow-up, he is curious if the changes in the aforementioned measurements are statistically significant. Which of the following is the most appropriate statistical method to compare the groups?"n"Impact of pulmeharkimab on asthma control and cardiovascular disease progression in patients with coronary artery disease and comorbid asthma\nIntroduction:\nActive asthma has been found to be associated with a more than two-fold increase in the risk of myocardial infarction, even after adjusting for cardiovascular risk factors. It has been suggested that the inflammatory mediators and accelerated .....

A: Pearson correlation analysis  
 B: Chi-square test  
 C: Analysis of variance  
 D: Meta-analysis  
 E: Kaplan-Meier analysis

**Most important features**

- \*\*Standard error\*\* is \*\*greater\*\* in the \*\*150 mg/day\*\* group.
- The question is asking for the \*\*reason\*\* for this increased standard error.
- The options relate to \*\*interpretation of standard error\*\* in terms of \*\*sample size, validity, statistical significance, confidence intervals\*\*, etc."

**Most important features**

- The goal is to determine \*\*statistical significance\*\* of \*\*changes\*\* in \*\*continuous variables\*\* (plaque volume, LDL-C, FEV1/FVC, ACO scores).
- The question is about \*\*comparing multiple groups\*\* (placebo vs. two doses of pulmeharkimab) on \*\*continuous outcomes\*\*.
- The data is \*\*normally distributed\*\* (as stated in the abstract).

**Correlation between Questions**

Both questions refer to the \*\*same study abstract\*\*.

- The first question is about \*\*interpretation of standard error\*\* (which relates to sample size and variability).
- The second question is about \*\*statistical method\*\* to determine \*\*significance\*\* of group differences.
- The \*\*sample size\*\* is a \*\*key factor\*\* in the first question (which explains the standard error).
- The \*\*ANOVA\*\* is the correct method in the second question, given that it is a \*\*randomized controlled trial\*\* with \*\*multiple continuous outcomes\*\*.

### Final Answers:

- \*\*Question 1 (Index: 1):\*\* \*\*D\*\*
- \*\*Question 2 (Index: 2):\*\* \*\*C\*\*

Figure 5: Example of LLM output for two questions with cosine similarity 0.9020 (embedding by Qwen3-4B embedding) given our prompt. Both questions refer to the same study abstract. The first question is about interpretation of standard error (which relates to sample size and variability). The second question is about statistical method to determine significance of group differences.

**Near-duplicate clinical stems (cosine = 0.9612).** Figure 4 shows two stems that are clinically indistinguishable with respect to decisive features (symptoms, exam, labs, biopsy). The only difference is age, which is *not* determinative for the underlying mechanism queried. Under the metric-fair constraint, the model maps both (question, option) pairs to nearby points in the half-space and selects the same correct option, *Adverse effect of anesthetic*. This demonstrates: (i) **individual fairness**: similar items receive similar scores/decisions; (ii) **demographic robustness**: age is ignored when it is not clinically decisive; and (iii) **boundary stability**: small semantic perturbations do not flip the decision.

**Shared evidence, different foci (cosine = 0.9020).** In Figure 5, both stems reference the same study abstract but ask distinct, yet related questions: one on interpretation of the standard error (sample size/variability), the other on choosing an inferential method for group differences. Joint presentation encourages the model to: (a) build a single internal representation of the study's statistical structure; (b) project each item to the appropriate decision subspace (interpretation vs. method); and (c) preserve cross-item *consistency* (e.g., larger  $n$   $\Rightarrow$  smaller SE; appropriate test tied to design/assumptions). The pairwise setting reduces near-boundary errors that arise when interpreting an abstract in isolation.

**Trauma mechanism coherence (cosine = 0.8314).** Figure 6 presents two trauma cases with shared mechanism (unrestrained MVA) and overlapping findings (chest wall bruising; hemodynamic/ECG

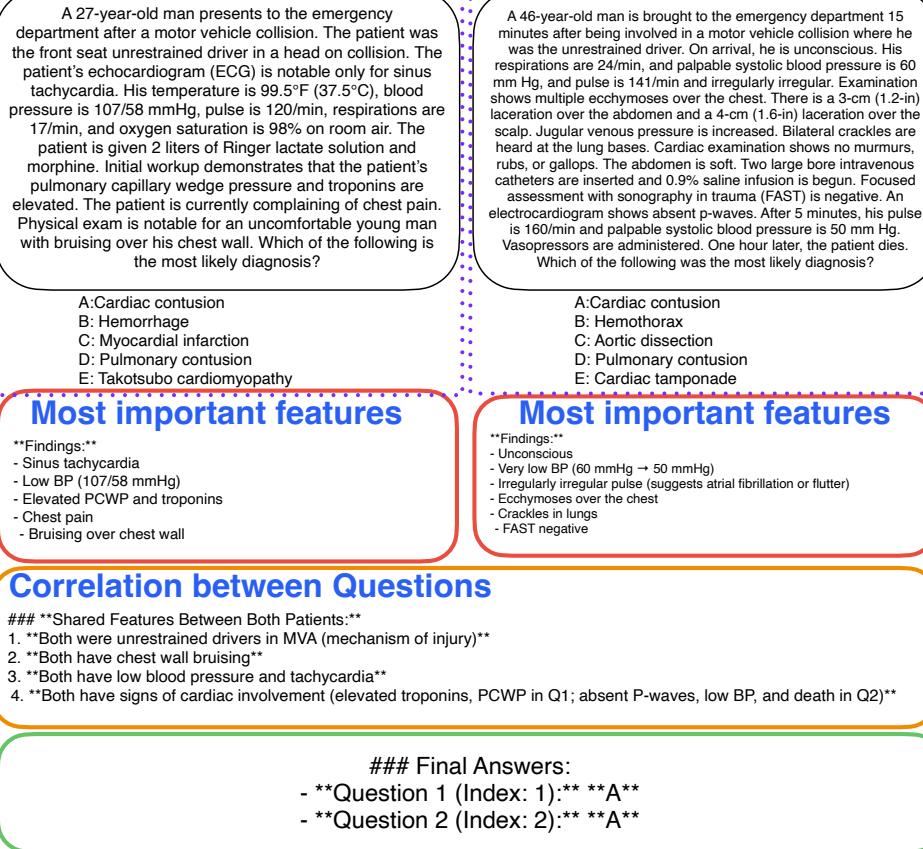


Figure 6: Example of LLM output for two questions with cosine similarity 0.8314 (embedding by Qwen3-4B embedding) given our prompt. Cardiac contusion (Option A) is the only option that is plausible in both cases, given similar mechanism of injury (unrestrained MVA), chest wall bruising, Elevated troponins (Q1), Cardiac dysfunction, Absence of other clear causes like MI or aortic dissection. The correct answer is same for both questions.

abnormalities). Among the options, *Cardiac contusion* (A) is uniquely plausible across both stems, consistent with elevated troponins or LV dysfunction and the absence of signs pointing to MI or dissection.

The model aligns both answers, reflecting: (i) **mechanism-level similarity** captured by embeddings; (ii) **margin reconciliation** across items (selecting the option that remains viable in both contexts); and (iii) **fairness by similarity**: clinically equivalent trauma patterns map to consistent outcomes.

**Methodological notes.** For each question  $q$ , we retrieve its nearest neighbor  $q'$  by cosine similarity on normalized sentence embeddings. The pair  $(q, q')$  is fed to the LLM with the joint protocol (Table 2). The model internally clusters decisive features, eliminates clear negatives (large negative margins), and resolves near-boundary options while enforcing a Lipschitz-like stability: if  $d(q, q')$  is small, then the score difference  $|f(q) - f(q')|$  remains small, promoting consistent outputs unless contradicted by a decisive discriminator (e.g., a contraindication).

**Fairness and robustness.** Across the examples, demographic attributes (e.g., age) are used only when explicitly clinically determinative; otherwise they are down-weighted by the prompt's fairness guard. The pairwise setting serves as a *regularizer* against spurious cues: when two similar items

are solved jointly, option choices that are inconsistent across the pair are penalized by the metric constraint, improving reliability on near-boundary decisions.

## 5 Related Work

There is a growing body of work attempting to study the question of algorithmic discrimination. This literature is characterized by high-level distinction, group and individual notions of fairness. We also introduce the prompt engineering related works.

Individual fairness posits that “similar individuals should be treated similarly” [6]. This powerful guarantees is formalized via a Lipschitz condition on the classifier mapping individuals to distributions over outcomes. Recent works study different individual level fairness in the contexts of reinforcement and online learning. study different individual level fairness in the contexts of bandit [11]. [17] studies metric-fair active learning of homogeneous halfspaces [16, 15], and show that under the distribution-dependent PAC learning model. Fairness and label efficiency can be achieved simultaneously.

Group fairness notions assume the existence of a protected attribute (e.g. gender, race), which induces a partition of the instance space into some small number of groups. A fair classifier is one that achieves parity of some statistical measure across these groups. There are prominent measures include classification rates (statistical parity [7], calibration, and false positive or negative rates [8]. [23] incorporating the fairness notion of [8] into a statistical and computational theory of learning, and proposed a relaxation of the fairness definition to make it feasible to optimize the learning objective.

LLMs are known to have already absorbed rich commonsense that makes it possible to propose reasonable plans conditioned on problem setting [4, 9, 20]. The idea of Chain-of-Thought is to enrich the few-shot examples with reasoning steps [22]. There are many studies to improve the performance of DoT on complex tasks such as dynamic least-to-most prompting [5], active Prompt [4]. Tree of thought approach extends planning formulations by considering multiple potentially feasible plans simultaneously at each problem-solving step [24]. [13] introduced the “self-reflection” mechanism, LLMs provide feedback to their generation candidates. [12] introduces review steps cover the actions and states, deciding the next action. “self-guided decoding” followers a tree-search procedure with leaves sampled from stochastic beam search decoding. Our prompt teaches LLMs to think like a machine learning algorithm with constraint and objective function, the constraint is the fairness metric [19]. [14] embeds LLMs in an algorithmic search procedure to help solve problems like question answering step-by-step, in which relevant paragraphs that might provide answers.

## 6 Societal Impact and Limitations

We believe that this work will have positive societal impact as it provides a new approach for using LLMs in healthcare with fairness property. One potential limitation of this work is that the performance is not completely understood from a rigorous theoretical perspective. Also, despite the observed gains, results are *not always stable*. Future work will: (i) improve stability via calibrated decoding, temperature-free beam search, and ensembling; (ii) learn task-specific similarity metrics with clinical supervision; (iii) integrate confidence estimation and selective answering; (iv) study pair construction beyond nearest neighbors (e.g., cluster-then-cover, active pairing); (v) evaluate on broader datasets and multilingual settings; and (vi) incorporate human-in-the-loop review and bias audits. These steps aim to strengthen reliability, fairness, and generalizability while keeping the method practical and transparent.

## 7 Acknowledgments

This research was supported in part by the Intramural Research Program of the National Institutes of Health (NIH). The contributions of the NIH authors are considered Works of the United States Government. The findings and conclusions presented in this paper are those of the authors and do not necessarily reflect the views of the NIH or the U.S. Department of Health and Human Services. Jie Shen is supported by NSF-AF-2239376 (CAREER award).

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